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A FIELD EXPERIMENT ON SEARCH COSTS AND THE FORMATION OF SCIENTIFIC COLLABORATIONS

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Abstract—We present the results of a field experiment conducted at Harvard Medical School to understand the extent to which search costs affect matching among scientific collaborators. We generated exogenous variation in search costs for pairs of potential collaborators by randomly assigning individuals to 90-minute structured information-sharing sessions as part of a grant funding opportunity. We estimate that the treatment increases the probability of grant co-application of a given pair of researchers by 75%. The findings suggest that matching between scientists is subject to considerable friction, even in the case of geographically proximate scientists working in the same institutional context.

I. Introduction

THE primary unit of scientific knowledge production has become the team or collaboration rather than the lone scientist (Jones, 2009). Indeed, teams are not only growing in frequency, but also in size and impact relative to single authors (Wuchty, Jones, & Uzzi, 2007). Unlike settings inside firms, where executives and managers play a central role in organizing and forming teams (Lazear & Shaw, 2007), academic scientists have greater freedom and autonomy in selecting their collaborators and their topics of inquiry (Stephan 2012). Although there is a growing body of research on the productivity and outcomes of scientific teams once formed (e.g., Adams et al., 2005; Wuchty, Jones, & Uzzi, 2007; Agrawal, Goldfarb, & Teodoridis, 2016), we know relatively little about the largely decentralized process by which scientific teams come into existence (Stephan, 2012). In this paper, we investigate the role of one particular mechanism, search costs and frictions, on these matching outcomes.

The role of search costs and resulting frictions in the formation of scientific collaborations is not well understood. On the one hand, the growing prominence of teams and falling communications and collaboration costs in science (Agrawal & Goldfarb, 2008; Ding et al., 2010) might suggest forces favorable to novel team formation. On the other hand, geography and distance are regularly documented to play a role in shaping collaborations, even today (e.g., Rosenthal & Strange, 2001; Glaeser, 2010, Catalini, 2016), and rather than continually forming novel collaborations, scientists most often work with partners in the same institution, in a similar knowledge domain, and within preexisting social networks (Baccara & Yariv, 2013; Freeman, Ganguli, & Murciano-Goroff, 2015; Freeman & Huang, 2014; Fafchamps, Goyal, & Van der Leij, 2010; Azoulay, Liu, & Stuart, 2009). Moreover, past collaborations remain an important predictor of future ones. Although these patterns might be explained by any number of factors, they raise the question of whether search costs play a first-order role in shaping the organization of scientists into teams.

The high information requirements for forming matches suggest that search frictions may be an important consideration. A large number of factors can play a role in decisions to collaborate, and these factors may be nuanced or difficult to observe. This includes factors such as the complementarity of skills of prospective partners, current research interests and priorities, access to broader sets of relevant resources (funding, equipment, research personnel), timing and scheduling constraints, and personal chemistry and disposition

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(Stephan, 2012). If acquiring and evaluating this information is costly, significant search frictions will appear, as has been found in other matching markets (Mortensen & Pissarides, 1999). Observed patterns of collaboration might then be interpreted as reflecting limited information in decision making—and therefore may constitute a suboptimal allocation of human resources.

To understand whether and to what extent search costs can affect the formation of collaborations among research collaborators, we carried out a field experiment with the goal of introducing exogenous variation in the information available to research scientists concerning potential collaborators. Our research team worked closely with Harvard Medical School's (HMS) clinical and administrative executives to modify and redesign existing internal grant processes so that causal inferences could be drawn in the context of an $800,000 grant opportunity for researchers at Harvard University and the HMS system of hospitals and research centers to encourage the development of clinical applications of advanced medical imaging technologies.

The field experiment involved designing a research symposium (repeated on three consecutive nights) that was part of the grant process, where investigators were to get details about the grant rules and administration, learn about advanced technologies underlying the grant, and meet other researchers through structured information-sharing sessions. Participation in one of the symposia (and only one) was mandatory for submitting a grant application, which was due four weeks after the symposia. Each symposium consisted of a 30-minute general introduction followed by 90 minutes of information sharing in independent and physically separated breakout rooms. Breakout rooms facilitated face-to-face interactions by having half of the researchers circulate about the room while the other half "broadcast" their research ideas in a standardized poster format. We reduced the cost of initial face-to-face interactions for random subsets of scientists by randomly assigning the roughly 400 researchers who took part to independent breakout rooms. Therefore, we can evaluate the effect of the treatment by simply comparing the likelihood of collaboration for pairs of researchers assigned to the same room (treatment) with the likelihood of pairs assigned to different rooms (control).

It is important to note that estimates of search costs in this context might be interpreted as occurring under best-case conditions. We study prospective collaborators operating within a shared institutional context, with potential funding availability, within the same geographic area, and in a context in which information systems and tools facilitate the search for prospective collaborators.

Yet our results suggest that matching between scientists is subject to considerable frictions even in this best-case context. We estimate that assignment to the same breakout room increased the probability of forming a collaboration by 75%, increasing the probability from 0.16% in the control group to 0.28% in the treatment. We estimate the effect to be significant at the 5% or 10% level, depending upon model specification. (The 95% confidence interval around the point estimate ranges from −4% to −112%.) To put this into perspective, the point estimate of the treatment effect is about one-third of the effect of working in the same hospital or of performing research in the same clinical area. This is a substantial effect for what is arguably a relatively small (90-minute information sharing) treatment.

This main finding is consistent with the view that large search costs and frictions play a first-order role in shaping the process of searching for collaborators and suggests the important function of information-rich face-to-face encounters in catalyzing collaborations. Consistent with the interpretation of a significant effect of search costs, the treatment effect was especially strong for pairs of researchers working in the same clinical area, where presumably search costs might be construed as lower given similar backgrounds and training. The findings therefore suggest the possibility that current observed patterns of collaborations in academic science are perhaps highly constrained by the availability of information and search costs. This is plausibly an important source of inefficiency. However, we cannot observe implications of this inefficiency within this analysis.

The finding of the first-order role played by search costs also offers one plausible explanation for the prevalence of homophily (McPherson, Smith-Lovin, & Cook 2001; Currarini, Jackson, & Pin 2009) in forming collaborations, where like scientists tend to coauthor, and repeatedly, as both tendencies may economize on search costs. The findings also imply potentially important differences between the formation of collaborations versus the execution of distributed collaborations. The formation and execution of collaborations may be considered as representing altogether different kinds of coordination problems—one of matching and the other of joint production. Whereas evidence suggests research collaborations may be able to be carried out at a distance through decreased communication and travel costs and increasingly sophisticated collaboration platforms (see Agrawal & Goldfarb 2008; Jones, Wuchty, & Uzzi 2008; Adams et al., 2005; Catalini, Fons-Rosen, & Gaule 2016), the process of forming collaborations may still be especially highly influenced and informed by information-rich, interpersonal interactions.

The paper proceeds as follows. We first describe our experimental design, including details of the grant program and research symposia in section II. In section III, we describe the data. The empirical strategy and results follow in sections IV and V, respectively. Section VI concludes.

II. The Field Experiment

A. *Harvard Medical School and Its Affiliated Hospitals*

Our field experiment involved faculty and researchers from Harvard University and its affiliated hospitals and

institutions. Harvard Medical School and its seventeen affiliated hospitals and research institutes (including Massachusetts General Hospital, Children's Hospital Boston, Brigham and Women's Hospital, Beth Israel Deaconess Medical Center, and the Dana-Farber Cancer Institute) are a major force in biomedical research. Collectively, they employ more than 11,000 faculty and receive in excess of $1.5 billion in annual funding from the U.S. National Institutes of Health (NIH). Harvard researchers account for around 5% of scientific articles published in the top four medical journals, a larger share than Germany or Canada as a whole.[1] Fifteen researchers have shared in nine Nobel prizes awarded for work done while at Harvard Medical School.

While our experiment is set entirely within the Harvard University system, in fact its researchers work in distinct organizations and research centers. The Harvard-affiliated hospitals are separately owned and managed and appear as separate entities in hospital rankings and lists of NIH grant recipients. Four of the five largest hospitals are located in the Longwood Medical Area campus in Boston, while Massachusetts General Hospital has its own campus about 3 miles away (and approximately 20 minutes by institutional shuttle bus).

B. Harvard Catalyst and Advanced Imaging

Closing the gap between research findings and clinical applications ("bench to bedside") is a major priority for the NIH. This has resulted in the establishment of a new institute, National Center for Advancing Translational Sciences, that provides significant research funding to universities and hospitals that undertake collaborative translational activities to accelerate treatment development. As part of Harvard's efforts to promote clinical and translational research, the Harvard Clinical and Translational Center, Harvard Catalyst, provides seed funding in the form of pilot grants to support nascent research efforts. These pilot grants are awarded competitively to faculty within Harvard University. They emphasize early-stage research with the potential to improve human health. Pilot grant funding enables researchers to generate the preliminary data that are essential for larger grant applications to the NIH.

Our field experiment was layered onto a Harvard Catalyst pilot grant program. This particular grant opportunity, which offered $50,000 per award, was centered on proposals to devise or improve methods for using advanced medical imaging technologies—specifically, physiological magnetic resonance (MR), positron emission tomography (PET), and optical imaging—to address unmet clinical needs. A major challenge in the field of advanced imaging is that progress requires both expertise in the latest imaging tools and technologies and a deep understanding of the health problems to which they could be applied, with these different types of knowledge typically being held by people with different disciplinary backgrounds. Thus, advanced imaging is an archetypical example of a problem often found in modern science where advancing the knowledge frontier requires combining knowledge embodied in different individuals (Jones, 2009).

We worked in close collaboration with HMS administrators and executives to redesign their pilot grant process so that we could obtain causal inferences about the role of search costs in finding collaborators. While the grant process was primarily focused on identifying and funding promising early-stage translational research in the field of advanced imaging, Harvard Catalyst leaders also perceived a need for familiarizing clinicians with recent developments in advanced imaging and for Harvard-wide community building among researchers. This provided us with the opportunity to create a new interactive research symposium where we could exogenously shift search costs for certain pairs of individuals by building in randomized face-to-face interactions. Hence we modified the Harvard Catalyst grant process by requiring potential applicants to attend an interactive research symposium that would be a forum to learn about new technologies, understand the grant process, and exchange ideas among fellow researchers across Harvard. This was the first time such an interactive Harvard-wide symposium on a new research grant opportunity was offered.

In November 2011, all Harvard University life sciences faculty and researchers were invited to participate in a unique funding opportunity centered on advanced imaging technologies using a directed e-mail campaign, outreach to departmental clinical and research directors, and marketing messages on various internal websites and through posters across facilities. Up to $800,000 was available to support fifteen pilot grants. There was the additional potential for researchers to apply for several concept development prizes of $2,000 each. The concept prizes were meant to stimulate innovative thinking and future investigation in areas in which imaging had not been previously considered as an intervention and did not require any implementation plan.

In the first stage, investigators who were interested in applying for the grants were asked to submit a statement of interest in which they briefly described a specific medical problem that advanced imaging techniques could potentially address. Basic biographical information (e.g., degree, institution, department appointment) was collected at this stage. Information distributed about the funding opportunity specified that eligibility to submit a final application was conditional on attending an advanced imaging symposium on one of three preannounced dates. Applicants could indicate at this stage if there were any dates during which they could not attend a symposium. It was also communicated to applicants that the symposia would be studied by Harvard Catalyst to develop better insights about scientific team formation and that data on interaction patterns among individuals would be collected.

[1] Journals included are the *New England Journal of Medicine, Journal of the American Medical Association (JAMA), Nature Medicine*, and *Lancet*. Authors' calculations based on research articles published during from 2000 to 2009. Fractional counting was used when coauthors belonged to different institutions.

C. Randomization and the Advanced Imaging Symposium

The initial call generated 471 statement of interest applications, of which 435 applicants were invited to attend an advanced imaging symposium and thus proceed in the grant application process.[2] Forty-one applicants (9.4%) failed to RSVP or otherwise show up at the event.[3] Invitations were also extended to several individuals with world-class expertise in advanced imaging, bringing the total number of participants to 402.

The symposium was structured so that participants would come to the event prepared to discuss their idea with other participants in small breakout rooms of thirty to forty people. The treatment was intended to introduce exogenous variation in search costs to some pairs of participants at the symposium by having them be present in the same breakout rooms at the event. Each participant was randomly allocated to a breakout room in advance so that a random subset of all possible pairs among all participants would receive the treatment. Three symposia were held on sequential nights and were identically structured, with four breakout rooms per night.[4] We also randomized the participants across nights; however, we respected the blackout dates for which applicants had previously indicated they would not be available.[5]

The events were held January 31, February 1, and February 2, 2012, at the Harvard Innovation Lab, located on Harvard's Allston campus. The program began with a 30-minute address by the program leadership describing the pilot grant opportunity and the agenda for the evening, including an introduction to advanced imaging tools and technologies. The breakout sessions then began in separate rooms. The number of participants in each room varied from 28 to 43.

The breakout room sessions were split into two periods of 45 minutes each, with a 15-minute break in the middle during which all participants could mingle in a common space where refreshments were provided. The rooms provided a venue for presentation of the participants' ideas in the form of posters. Each poster followed a standard format describing each participant's submitted idea from the statement of interest (based on information they had provided prior to the event) and was placed in the breakout room in advance.[6] The posters were intended to foster information sharing among participants and included the following details related to the statement of interest idea: (a) What is your question? (b) Why does it matter? and (c) What is needed for your research to succeed? A 300-character limit was imposed for each question. Posters were prepared in a standard size and format by Harvard Catalyst, and each was placed on a separate whiteboard that allowed for the possibility of visual explanations and note taking.

Participants within each breakout room were randomly split into two groups. Participants from group 1 were asked to stand by their poster during the first period, while group 2 participants circulated. The two groups then switched roles during period two: group 1 participants circulated around the room, while group 2 participants stood near their own posters. The placement of each individual's poster in the room was also randomly determined in advance.

D. Grant Applications

Shortly after the symposia, all participants received via e-mail an invitation to submit applications for the pilot grants or concept awards by the deadline of March 8, 2012. At this time, they also received PDF booklets with the names, contact information, and posters of all researchers who participated over the three nights.[7] Note that as of 2008, Harvard Catalyst had already deployed the Harvard Catalyst Profiles website, an online, publicly accessible interactive database that includes contact information, current appointments, individual publication records, and other information for faculty and researchers across Harvard Medical School, and can be searched by name or keyword. Thus, much of the information contained in the PDF booklet could already easily be acquired online. However, the booklet also included information on current research interests, related to the grant, that was less easily available; the booklet may also have increased the salience of the publicly available information for the included individuals. Our intention was to provide identical information to all participants apart from information acquired specifically in the breakout rooms at the symposia.

Consistent with previous Harvard Catalyst pilot grant processes, applications had to include a principal investigator and at least one co-investigator. Concept award applications similarly had to include at least two individuals. Researchers with faculty appointments could apply as principal investigator on only one pilot grant but could apply as

[2] Thirty-six statements of interests were outside the parameters of the request for applications in terms of area of inquiry (e.g., proposing ultrasound or X-ray computed tomography [CT] techniques) and the submitters were not invited to attend the symposium.

[3] We do not include these individuals in the analysis.

[4] The randomization was carried out by generating a unique random number for each participant, ranking the numbers, and then assigning participants to breakout rooms on nights based on their rank. We assigned 32 participants to the first three rooms each night, and the remainder (41–48) to the last room, which was slightly larger.

[5] Participants with blackout dates were a minority, but to guard against the potential endogeneity of selection into nights for this group, the analysis focuses on comparisons within nights.

[6] Participants were provided with the following information in the e-mailed invitations to attend a symposium: "You do not need to bring any particular items with you. We have a poster prepared with your submitted answers to the three questions based on your statement of interest. Posters will be displayed at the symposium to facilitate talking about your idea with other attendees. There will be no formal presentations of any kind."

[7] The following information was included in e-mail communication with participants immediately following the event: "Attached to this email is a PDF booklet with the names and contact information of all researchers who participated over the three nights and their posters. We hope this is of use in contacting individuals that you met during the evening and in identifying additional potential collaborations and collaborators. . . . As described at the symposium, your proposal or your collaborators can be the same as suggested in your Statement of Interest or can be somewhat or entirely different. You can participate in multiple applications."

co-investigator on an unlimited number of additional applications. Researchers without a faculty appointment could not be principal investigators on a pilot grant application, but they could be co-investigators on an unlimited number of applications. All attendees were eligible to apply for a concept award grant and could appear on an unlimited number of applications. Finally, at least one applicant on any grant application had to have attended the symposium. The grant application did not need to be based on the initial statement of interest.

Extra care was taken to ensure that the symposium process did not somehow prime participants to seek collaborations only in their breakout rooms. Participants were informed that the composition of their teams would not be communicated to reviewers and would not be considered as a criterion for awarding the grant. They were also told to remove any personal identifying information about the submission teams from their proposals (including self-references and indications of special access to technologies).[8] This differed from the typically single-blinded process used in NIH and Catalyst grants, in case the identification of submission applicants might have an impact on collaboration choices. In the end, the majority of participants chose not to apply with other symposium participants: 66% of the applications included only one symposium participant as a coapplicant.

III. Data

A. Sources and Construction

Registration data. Faculty and researchers interested in taking part in the funding opportunity were asked to submit a short statement of interest describing in 250 words or less a specific medical problem that advanced imaging techniques could potentially address. Registration data also included basic biographical information (rank, education history, hospital affiliation, department). Participants were also asked to identify themselves as primarily an imager or primarily a clinician. Clinical area and imaging modality were coded from the statement of interest documents.

Publications. We matched participants to Harvard Catalyst Profiles, an online, publicly accessible database that includes individual publication records and other information for faculty and researchers across Harvard Medical School.

Grant applications. Our main outcome variable comes from the pilot grant and concept award applications. We received 224 applications for pilot grants or concept awards.[9] Of those, 148 included one symposium participant in the applicant list, 49 included two symposium participants, and 27 included more than two symposium participants.

Table 1.—Summary Statistics, Attendees

	Sample Mean
Female	0.29
Faculty member	0.73
Imager	0.42
Longwood	0.51
Hospital	
Massachusetts General Hospital	0.37
Brigham and Women's Hospital	0.19
Beth Israel Deaconess Medical Center	0.14
Children's Hospital Boston	0.13
Other	0.17
Clinical area (SOI)	
Neurology	0.25
Oncology	0.25
Neuropsychiatric	0.10
Cardiovascular	0.06
Gastroenterology	0.04
Transplantation	0.04
Ophthalmology	0.03
Other	0.23
Attended January 31	0.35
Attended February 1	0.32
Attended February 2	0.33
Observations	402

See section III in the text for a detailed description of the variables.

Constructing the pair-level data. Our analysis is conducted at the dyadic level. We constructed dyads by creating every possible pairwise combination of researchers attending a symposium on the same night (26,604 dyads). We constructed our main outcome at the dyadic level, collaboration, from grant applications. A collaboration was defined as any pairs of symposium participants appearing on the same application. In some parts of the analysis, we restricted our sample to the 52 pairs of scientists who attended on the same night and coapplied. We also constructed a number of dyadic-level control variables from the registration and publication data, which are described in more detail in section IV.

B. Summary Statistics and Randomization Check

Table 1 provides individual-level summary statistics for symposium participants.[10] Of the 402 attendees, 29% were women, 42% identified themselves as imagers, and 73% held Harvard faculty appointments (the others were postdoctoral fellows or clinical fellows). Over 80% of attendees came from the four largest Harvard-affiliated hospitals: Massachusetts General Hospital (MGH), Brigham and

[8] The following directions to applicants were highlighted in the grant request for applications: "As the initial review will be blinded in regard to the applicant(s), do not refer to yourself, other participants or institutions by name (e.g., substitute 'our optical imaging experts,' 'our cardiology collaborators,' 'our laboratory' or 'the genomics core' for specific individuals or facilities)."

[9] Seventy-eight percent of applications were for pilot grants, and 22% were for concept awards.

[10] Across the three nights, 394 individuals were in attendance. However, 5 people with special expertise in advanced imaging attended the event on more than one night; we count them as different participants on each night, bringing the total number of participants to 402.

TABLE 2.—DYADS BY TREATMENT STATUS

Sample Means	Treatment: Same Room	Control: Different Room	Difference
One postdoc	0.404	0.396	−0.007
Both postdocs	0.072	0.075	0.003
One female	0.403	0.418	0.015*
Both female	0.085	0.082	−0.004
Same hospital	0.198	0.208	0.010*
Both Longwood	0.266	0.258	−0.010*
One imager + one clinician	0.492	0.489	−0.003
Both imagers	0.175	0.176	0.001
Same clinical area (SOI)	0.123	0.119	−0.004
Previous coauthor	0.001	0.002	0.001*
Observations	6,702	19,962	

The unit of observation is a dyad of researchers. We construct dyads by creating every possible pairwise combination of researchers attending on the same night (26,604 dyads). The category *Treatment: Same Room* refers to participants in the same room at the event; it was randomized across pairs of participants attending on the same night. *Collaboration* indicates whether the pair appeared on any common pilot grant or concept award applications. See section III for a detailed description of the variables. Asterisks indicate the results of tests for equality of means. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Women's Hospital, Children's Hospital Boston, and the Beth Israel Deaconess Medical Center. The most prevalent clinical expertise areas were neurology (25%), oncology (25%), and neuropsychiatry (10%).

We can also compare the participants to the general population of researchers at Harvard Medical School. Appendix table A1 provides summary statistics on participants and nonparticipants based on information in the Harvard Catalyst Profiles database. In terms of degree types, there was no significant difference in the share of MDs among attendees and the overall HMS population, but there was a larger share of PhDs among attendees (49% PhDs among attendees versus 38% at HMS). We would expect a greater representation of PhDs at the event since it was part of a research grant opportunity, and academic PhDs are very often focused on research, while academic MDs have a larger array of potential roles. Attendees also had more prior publications on average (approximately four publications more than the typical HMS researcher). We also see some significant differences in the distribution across ranks, with attendees more likely to be instructors and assistant or associate professors relative to the overall distribution at HMS and less likely to be full professors and postdocs. Attendees were also more likely to come from MGH. One reason for this is that MGH houses a large advanced imaging center, the Martinos Center for Biomedical Imaging, and the focus of the grant opportunity was advanced imaging. For the same reason, individuals from radiology departments were overrepresented among attendees.

To verify that the randomization generated balance across covariates, we present summary statistics in table 2 for the pairs in our sample assigned to the same breakout room and those assigned to different breakout rooms. The unit of observation here is a dyad of researchers, and the sample is every possible pairwise combination of researchers attending on the same night (26,604 dyads). Treated pairs and control pairs look very similar, with the exception of pairs of previous coauthors, pairs with both members from the same hospital, and pairs including one woman, which are statistically different across treated and control pairs.[11] In our regression analysis, we control for these covariates.

The last row of table 2 includes collaboration, our outcome variable. The incidence of collaboration is significantly larger in the treated group, which we investigate in a regression framework in the next section. It is notable that the incidence of collaboration is less than 0.2% in our sample. While this may seem low, the likelihood that any two HMS faculty members will copublish in a given year is 0.06% and, thus, of the same order of magnitude.[12] Viewed through the lens of all pair-wise combinations of scientists who could collaborate, collaboration is indeed a relatively rare event.

Table 3 shows the characteristics of the subset of collaborating dyads. Here we restrict the sample of every possible pairwise combination of researchers attending on the same night (26,604 dyads) to those who coapplied (52 dyads). Among attendees who attended on the same night but were not in the same breakout room, 33 pairs coapplied. Among pairs in the same room at the event, 19 pairs coapplied.[13] *T*-tests show that among the same-room collaborations, there was a higher incidence of pairs with one postdoc and of pairs researching the same clinical area. It is important to note that some of the within-room collaborations would have occurred in the absence of any treatment effect. Extrapolating the across-room incidence rate (0.16%) to the number of within-room pairs (7,149), we would expect eleven collaborations to have occurred within rooms in the absence of any treatment effect.

[11] The relatively large difference between the percentage of pairs of previous coauthors across treatment and control groups can be explained by the very small number of pairs of previous coauthors in our sample (40 out of more than 20,000). Thus, randomization could easily result in a different incidence of pairs with coauthors across treatment and control groups, as it did in our case.

[12] Authors' calculation based on publication data from Harvard Catalyst Profiles.

[13] The nineteen pairs who coapplied from the same room correspond to eighteen separate grant applications.

TABLE 3.—COLLABORATING DYADS BY TREATMENT STATUS

Sample Means	Collaborations within the Same Room	Collaborations across Rooms	Difference
One postdoc	0.421	0.212	−0.209
Both postdocs	0.000	0.030	0.030
One female	0.474	0.303	−0.140
Both female	0.158	0.061	−0.097
Same hospital	0.579	0.636	0.057
Both Longwood	0.158	0.303	0.145
One imager + one clinician	0.474	0.485	0.011
Both imagers	0.316	0.394	0.078
Same clinical area (SOI)	0.579	0.273	−0.306**
Previous coauthor	0.105	0.121	0.016
Observations	19	33	

The unit of observation is a dyad of researchers. We construct dyads by creating every possible pairwise combination of researchers attending on the same night (26,604 dyads), but here we focus on researchers who attend on the same night and appeared on a common pilot grant or concept award application (52 dyads). See section III in the text for a detailed description of the variables. Asterisks indicate the *r*esults of *t*-tests for equality of means. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

IV. Estimation Strategy

A. Specification

We use the simplest possible estimation strategy to describe differences between treatment and control groups—and the effect of exogenous variation in search costs in our context. The approach of our statistical analysis is to study the incidence of collaborations among all possible pairs of participants attending on the same night within our experimental group of 402 individuals. This reduced-form approach suits our interest in studying the extent to which observed behaviors deviate from fully informed equilibrium outcomes.[14] This approach also allows us to deal with relatively small numbers of actual within-room collaborations in a most straightforward and conservative manner.

Thus, the unit of analysis is the scientist pair, and the data set includes every possible pair of scientists across all nights. We use a linear probability model to describe how the incidence or probability of collaborations differs across treatment and control groups (i.e., those in the same versus different breakout rooms). Random assignment of pairs within the research design allows us to interpret differences as causally related to exogenous variation in search costs. We are also able to regress the incidence of collaborations on other covariates of researcher pairs to further describe associations with the incidence of collaborations. To measure whether treatment effects varied across subgroups, we interacted *Same Room* indicator with pair-level variables.

Thus, to estimate the impact of being in the same room at the event on the likelihood of collaboration between pairs, we ran linear regressions with the following specification:

$$\begin{aligned} Collaboration_{ij} = {} & \alpha + \beta Same\,room_{ij} + \theta Same\,room_{ij} \\ & \times Distance_{ij} + \pi Distance_{ij} \\ & + \delta X_{ij} + \varepsilon_{ij}, \end{aligned} \tag{1}$$

where the key explanatory variable associated with the treatment effect, $Same\ Room_{ij}$, is an indicator variable that equals 1 if both researcher i and j were randomly assigned to the same breakout room at the symposium.[15] $Collaboration_{ij}$ is an indicator variable for whether i and j appeared on any common pilot grant or concept award applications. X_{ij} is a vector of observable pair-level characteristics that can affect the likelihood of collaboration and includes measures of gender and professional rank. The vector $Distance_{ij}$ includes measures of differences in professional rank, as well as geographic, scientific, and past coauthoring, described below. The model also includes fixed effects for each night of the symposium.

The estimation of dyadic regressions raises an inference problem: dyadic observations may not be independent of each other as the same individual appears in many dyads. To address this inference problem, Fafchamps and Gubert (2007) have developed a network inference method adapted from spatial econometrics that corrects dyadic correlation of errors and also possible heteroskedasticity. We estimate and report equation (1) using an OLS regression with grouped dyadic standard errors according to Fafchamps-Gubert.[16]

[14] Structural matching models that contemplate competitive equilibria in matching are an alternative approach to modeling the equilibrium formation of collaborations. However, pursuing such an approach requires we make structural assumptions regarding equilibrium search process and outcomes—which goes against our interests in this study, given our interest in investigating frictions. Therefore, it is more appropriate in this instance to proceed with a reduced-form description of patterns to better describe any implications of search costs. Although this creates the possibility of downwardly biased estimates on the treatment effect, any such effect is likely to be vanishingly small: competition in matching is likely to have played only a small role, if much at all, as the absolute incidence of collaborations in these data is rather low and individuals were not limited in the number of collaborations they could form.

[15] There are several other ways to study and model search costs in this setting. We could, for example, study the effect of attending the symposium on the same night. Furthermore, since participants' posters were also randomized within the breakout rooms, we could study if immediate neighbors in the breakout room at the event had an impact on collaboration. However, neither of these approaches had a significant impact on our outcome of interest, grant coapplications.

[16] We implement this using the ngreg ado file available on Marcel Fafchamps's website: http://web.stanford.edu/~fafchamp/resources.html. Note that we obtain very similar standard errors and confidence intervals when using Eicker-White heteroskedasticity-robust standard errors instead. We do not cluster standard errors by night of attendance, since assignment to nights is itself random (conditional on blackout dates for a minority of participants) (Cameron & Miller, 2015).

B. Covariates

Several additional covariates describing pairs are also included in the model. Inclusion of these covariates should not affect the point estimate of the treatment effect but should increase its precision and offer further opportunity for interpretation. Our vector of pair-level covariates, X_{ij}, includes variables for gender and professional rank. Gender is captured by indicator variables *Both female, One female*, and *Both male*. Research indicates that women have a greater propensity to work with other women (Boschini & Sjogren, 2007) and more generally have more limited academic networks (see Ding et al., 2010). For professional rank, we include indicators for *One postoc* in the pair and *Both postdocs*. Postdocs were eligible to apply for either the concept or pilot grants; however, two postdocs could collaborate on a pilot grant application only if a third team member with a faculty appointment assumed the role of principal investigator.

The vector $Distance_{ij}$ includes measures of differences in professional rank and geographic, scientific, and past coauthoring. Given the potential relevance of these various forms of distance to search costs, coefficients estimated on these variables provide at least some broad and rough means of judging the importance of any estimated treatment effect by direct comparison with coefficients on these variables.

Distances in professional range are measured with indicator variables corresponding to possible combinations of differences. In relation to geographic distance, we create an indicator for *Same hospital*, which indicates whether pair members' primary appointments are in the same Harvard-affiliated hospital or institute. We also create an indicator for *Both Longwood*, indicating that both members of the pair work on the same campus,[17] as the largest concentration of researchers are located in hospitals and institutes either on the Longwood Medical Area (LMA) campus or at the MGH campus. The campuses are located approximately 3 miles apart (with a travel time of about 20 minutes during normal traffic). We also create a direct measure of geographic distance by geocoding exact locations of offices and calculating pairwise distances in miles.

In relation to scientific or intellectual distance, we create indicator variables for *Both imagers, One imager + one clinician*, and *Both clinicians*. We construct this variable using the information attendees themselves reported during the initial stage of the application process. We also constructed indicator variables for *Same clinical area* and *Same imaging modality* (physiological MR, PET, or optical imaging). These were coded from the statement of Interest documents submitted in the first stage of the application process. We also create measures of scientific distance using overlap in the Medical Subject Heading (MeSH) terms from each individual's publications and overlaps in the keywords of each individual's statement of interest.[18]

A final measure of distances is whether the pair had previously collaborated, indicator variable *Previous coauthors*. We also distinguish cases of one single past copublication with more than one past copublication with indicator variables.

Table 4.—Main Effect of Treatment on Collaboration

DV = Collaboration	(1)	(2)	(3)
Same Room	0.0012*	0.0012*	0.0014*
	(0.0007)	(0.0007)	(0.0007)
One postdoc			−0.0008
			(0.0005)
Both postdocs			−0.0014**
			(0.0007)
One is female			0.0002
			(0.0005)
Both are female			0.0010
			(0.0011)
Same hospital			0.0042***
			(0.0010)
Both Longwood			−0.0001
			(0.0007)
One imager + one clinician			0.0008*
			(0.0005)
Both imagers			0.0025**
			(0.0010)
Same clinical area (SOI)			0.0042***
			(0.0014)
Previous coauthor			0.1176**
			(0.0468)
Constant	0.0016***	0.0012***	−0.0010
	(0.0003)	(0.0004)	(0.0007)
Night fixed effects	No	Yes	Yes
R^2	0.000	0.000	0.017
Number of observations	26,664	26,664	26,664

The unit of analysis is a dyad of researchers. We construct dyads by creating every possible pairwise combination of researchers attending on the same night (26,604 dyads). The dependent variable is *Collaboration*, an indicator variable for whether the pair appeared on any common pilot grant or concept award applications. The main variable of interest is *Same room*, which was randomized across pairs attending on the same night. All estimation is by OLS. Grouped dyadic standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

V. Analysis and Results

A. Does Reducing Search Costs Increase the Propensity to Collaborate?

We first analyze whether our 90-minute breakout treatment had an effect on the incidence of collaborations and the magnitude of any such effects. OLS estimates with robust standard errors are presented in table 4. (The same results are presented using probit estimation in table A2.) Column 1 shows the basic result, regressing the incidence of collaborations on our treatment effect indicator and a constant. The baseline probability of collaborations is captured by the constant coefficient of 0.0016 or 0.16%. The point estimate shows that the treatment increases the likelihood of collaborating on an application by approximately 75% (increasing

[17] The LMA includes eight hospitals or institutes in our sample, and the MGH campus includes two hospitals or institutes. The other hospitals or institutes in the sample are considered to be individual campuses.

[18] We include these other measures of scientific distance in our regression analysis, but since these measures rely on prior publications (and some individuals in the sample have no or few publications), our preferred measure is self-reported clinical area.

the likelihood of a pair collaborating from 0.16% to 0.28%).[19] The estimate is significant at the 10% level.

The advanced imaging symposia were held on three different nights. We thus include fixed effects for the night of the event (January 31, February 1, or February 2) in column 2 to account for any differences across nights. The night fixed effects are not significant, and their inclusion has very little impact on the same room coefficient (or its standard error).

In column 3 we introduce pair-level variables to account for gender composition, differences in rank, as well as geographic, scientific, and past coauthoring distance. The random assignment ensures that being in the same room is orthogonal asymptotically to any observable or unobservable pair characteristic.[20] Correspondingly, introducing covariates does not statistically change the estimated treatment effect. The standard error is not palpably changed, but the significance marginally increases on account of a small increase in the point estimate. The point estimate for the effect of being in the same room increases slightly from 0.0012 to 0.0014. (Note that we also include additional controls in other specifications, including dummies for whether a pair was in the same group within a breakout room—group 1 or 2—and their proximity to one another in the room—whether the pair had posters next to each other—but the results do not change.)

We conclude this section by briefly discussing the sign of the point estimates of the control variables in table 4, column 3. Working in the same clinical area, being affiliated with the same hospital, and being a coauthor in the past are positively and significantly correlated with collaboration. Consistent with the related literature, these results suggest that geographic, scientific, and past coauthoring are all positively related to collaboration. Pairs of one imager and one clinician were significantly more likely to collaborate than pairs of clinicians only, but collaborations were even more likely to form when both members of the pair were imagers. Collaboration was significantly less likely to occur between pairs consisting of two postdocs, which is possibly explained by the fact that two postdocs could collaborate on a pilot grant application only if a third team member with a faculty appointment assumed the role of principal investigator. Overall, the single largest correlate is whether scientists had previously coauthored a publication. This association is at least an order of magnitude larger than for each of the other correlates.

Therefore, our estimated treatment effect of being in the same breakout room on collaboration is over 30% of the effect of being from the same hospital (0.0044) and of researching the same clinical area (0.0040). Relative to the single most important correlate, past coauthorship, it is only about 1% of the magnitude (0.1126). (The probit estimates in table A2 of the appendix show similar results.)

B. *For Which Pairs Does Reducing Search Costs Have the Greatest Effect?*

Next, we investigate whether the treatment had an effect for different types of pairs. Unlike earlier estimates of correlations with covariates, interaction terms can be interpreted causally. Probit estimates are reported in table A3 of the appendix. We introduce the interactions between covariates with the treatment effect individually in columns 1 to 7 and then simultaneously in column 8 of table 5. In introducing each of the interaction terms, we also of course reintroduce the direct effect of the covariate in the regressions; however, our focus here is on interactions terms.

In the results of columns 1 through 7, the only interaction term found to be significant is that in column 6, which reports a positive and significant coefficient on the interaction between the treatment effect and the indicator for researchers being in the same clinical area. The coefficient on the direct treatment effect term *Same Room* becomes statistically indistinguishable from 0 when introducing this interaction. Results in column 8 corroborate this result, as introducing all covariates and all interaction terms at once in the model produces an almost identical estimate on this interaction term. In column 8, which includes all interactions, the treatment increases the likelihood of collaborating for pairs researching the same clinical area from 0.35% to 0.94% relative to pairs researching different clinical areas.[21]

There are several possible explanations for the effect, but it suggests that researchers had limited information about these potential collaborations—about either the potential interest of other researchers in certain types of projects or the potential benefits of collaborating with these individuals. If they did, the information provided at the event should not have any independent effect for these pairs. It may also be the case that discussions were more beneficial for clinically proximate pairs because they shared common ground, allowing them to convert their discussions into collaborations. Another possible explanation is that it is quite costly to switch clinical areas (specialization and training in medicine occurs on the basis of clinical areas—e.g., dermatology, neurology, oncology), and therefore, even if researchers talked to people with interesting ideas in other clinical areas at the event, the benefits to collaboration were highest for those in the same clinical area.

We fail to detect evidence of the significance of other interactions. Our results on the interaction between being in the same room at the event and other pair characteristics are not

[19] However, our point estimates regarding the magnitude of the effect are imprecise. The confidence interval ranges from 4% to 112%.

[20] Being in the same room is orthogonal to pair characteristics ex ante. However, ex post, being in the same room at the event could be correlated with pair characteristics by chance. While this is much less of a concern than in observational data (Leamer, 2010), it is nonetheless useful to control for relevant, observable pair characteristics to address the possibility that the effect of being in the same room is affected by differences in observable pair characteristics. Introducing controls has the added benefit of improving the precision of the *Same room* estimate by reducing the unexplained variance.

[21] The sample average incidence of collaboration for pairs working in the same clinical area but not in the same room is 0.35.

TABLE 5.—TREATMENT AND INTERACTIONS WITH MEASURES OF DISTANCE

DV = Collaboration	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Room	0.0008	0.0000	0.0008	0.0018*	0.0012	−0.0000	0.0011	−0.0019
	(0.0009)	(0.0009)	(0.0006)	(0.0009)	(0.0009)	(0.0006)	(0.0007)	(0.0014)
One postdoc	−0.0016***							−0.0012**
	(0.0006)*							(0.0005)
Same room × One postdoc	0.0015							0.0019
	(0.0013)							(0.0013)
Both postdocs	−0.0016*							−0.0012
	(0.0008)							(0.0008)
Same room × Both postdocs	−0.0014							−0.0011
	(0.0011)							(0.0011)
One is female		−0.0008						−0.0004
		(0.0006)						(0.0006)
Same room × One female		0.0021						0.0024
		(0.0016)						(0.0015)
Both are female		−0.0007						−0.0000
		(0.0013)						(0.0013)
Same room × Both female		0.0040						0.0035
		(0.0025)						(0.0025)
Same hospital			0.0044***					0.0037***
			(0.0014)					(0.0013)
Same room × Same hospital			0.0024					0.0023
			(0.0026)					(0.0025)
Both Longwood				0.0005				0.0004
				(0.0007)				(0.0007)
Same room × Both Longwood				−0.0020				−0.0018
				(0.0014)				(0.0015)
One imager + one clinician					0.0009+			0.0008*
					(0.0005)			(0.0004)
Same room × One imager					−0.0000			−0.0000
					(0.0014)			(0.0012)
Both imagers					0.0031***			0.0025*
					(0.0011)			(0.0011)
Same room × Both imager					0.0002			−0.0002
					(0.0026)			(0.0025)
Same clinical area (SOI)						0.0025*		0.0018
						(0.0011)		(0.0012)
Same room × Same clin area						0.0095**		0.0094**
						(0.0045)		(0.0042)
Previous coauthor							0.0917*	0.0889**
							(0.0450)	(0.0442)
Same room × Prev coauthor							0.2389	0.2363
							(0.1981)	(0.1967)
Night fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.001	0.000	0.003	0.000	0.001	0.002	0.019	0.024
Number of observations	26,664	26,664	26,664	26,664	26,664	26,664	26,664	26,664

The unit of analysis is a dyad of researchers. We construct dyads by creating every possible pairwise combination of researchers attending on the same night (26,604 dyads). The dependent variable is *Collaboration*, an indicator variable for whether the pair appeared on any common pilot grant or concept award applications. The main variable of interest is *Same room*, which was randomized across pairs attending on the same night. All estimation is by OLS. Grouped dyadic standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

conclusive. While the point estimates for some interactions are positive, they are not significant up to the 10% level.[22]

We also investigated various alternative specifications such as including more finely grained measures of geographic distance, scientific distance, or past coauthoring,[23] as well as controlling more flexibly for ranks and rank differences between pair members. We included dummies for whether a pair was in the same group (1 or 2), proximity in the room (whether the pair had posters next to each other), and the number of total individuals in the room (to test whether density mattered), but the results were not significant, and the same clinical area result is consistent and stable across these specifications.

VI. Summary and Conclusions

Teams are a primary unit of knowledge production, and scientists in large part self-organize into research teams. Yet we know little regarding the matching of scientists into teams. In this paper, we present the results of a field experiment to investigate the role of search costs in the formation of scientific teams by comparing the incidence of collabora-

[22] The interaction between being in the same room and pairs with one woman are marginally significant with *p*-values of 0.093 in the probit specification and 0.133 in the OLS specification. A differential effect for pairs with a woman would be consistent with the findings of Ding et al. (2010), who show that the introduction of information technology benefited collaborations more for female scientists than for male scientists, since women tend to have less diverse networks, lower job mobility, and more constraints to attending conferences and seminars. These factors would similarly lead women to benefit more from mixing with other researchers at the event in terms of finding coauthors.

[23] We considered, for instance, whether pair members investigated the same imaging modality, the extent of the overlap of scientific keywords in previous publications, and whether pair members shared a common coauthor.

tions among researchers who participated in the same breakout rooms within an interactive research symposium as part of a grant proposal process versus those who were assigned to different breakout rooms. We thus randomly varied search costs for a set of prospective collaborators, observing both the collaborations that did form along with those that did not.

We find that the small, focused treatment significantly increased the incidence of collaboration on subsequent grant proposals by 75% in relation to the baseline probability of collaboration between pairs of researchers (increasing from 0.16% in the control group to 0.28% in the treated group). The magnitude of this effect is equivalent to roughly a third of the boost in the probability of collaboration associated with working in the same hospital or, alternatively, the probability of working in the same clinical area. In this regard, the point estimate can be viewed as rather large, despite the relatively small and focused nature of the treatment: a 90-minute breakout session. It is in fact notable that we find any effect at all, let alone such a large effect in the context of scientists who are already geographically proximate and working within a common institutional context, where online resources and information systems already exist to facilitate collaboration.

We interpret these large effects as showing that even when working in relatively favorable conditions, search costs and frictions continue to powerfully shape (and limit) the formation of collaborations between scientists. Whereas a great deal of collaborative work might potentially be performed at a distance, the formation of collaborations appears to be highly sensitive to information-rich face-to-face interactions. In this sense, the question of the "death of distance" and the role of collocation and information technology, for example, might be reconsidered at least in relation to questions of forming collaborations.

The finding is consistent with the complex and manifold set of variables on which collaboration decisions might be based and the effectiveness of face-to-face interactions in rapidly conveying information through high-frequency rapid feedback and visual and nonverbal cues (Gaspar & Glaeser, 1998; Storper & Venables, 2004). For example, given our existing communications technologies, it may remain difficult to wholly codify current research interests, complementarity in knowledge and skills, access to resources, and timing and scheduling constraints, let alone questions of personal chemistry and disposition or subtler questions of one's intellectual outlook. The result is also consistent with face-to-face interactions potentially triggering or credibly signaling commitments, establishing trust and personal chemistry (Azoulay et al., 2009).

Further consistent with the role of search costs in our results, the treatment effect was most pronounced on subsets of scientist pairs who are less distant, working within the same clinical area, and therefore perhaps needing to overcome lower information and search cost hurdles. We also found positive associations between the likelihood of forming collaborations as prospective collaborators coming from the same hospital, and the single most important predictor of collaborations, in terms of coefficient magnitude, was whether individuals had previously collaborated.

In documenting an important role played by search costs in influencing the formation of collaborations, we leave open a range of related questions. For example, in this paper, we did not study or observe longer-run outcomes of scientific productivity such as subsequent publications. (Initial analysis of reviewers' assessments of the grant applications indicates no statistical difference between scores of applications submitted by pairs in the same room versus pairs not in the same room at the event; see appendix table A4.) Also, we demonstrate what are arguably large effects of the particular treatment we implemented here. However, the treatment exploited here is not necessarily optimal and could be subject to further improvement. Such insights could be relevant in devising improved means of designing supporting information systems and matching facilities. An additional and potentially rather important series of questions falling outside the scope of this study concerns how individuals develop their own stock of matching-relevant information and heuristics in the first place (apart from effects of situational or episodic shocks in information, as were explored here).

The patterns documented here also raise questions regarding the extent to which homophily (Lazarsfeld & Merton, 1954; Baccara & Yariv, 2013) exemplified by increased likelihood for scientists to form ties with other scientists possessing similar personal characteristics, might, at least in large part, be the result of search costs—rather than reflecting collaboration preferences (Boudreau & Lakhani, 2012) or lower coordination costs when collaborating with similar partners (Reagans & Zuckerman, 2001; Reagans, Zuckerman, & McEvily, 2004).

Despite these limitations, we see this study as a step toward opening the black box of how scientific collaborations form. In recent years, there has been considerable interest in the policy arena in fostering collaborations, and especially interdisciplinary collaborations, in particular by the U.S. government agencies funding fundamental research and development (a combined budget of $36 billion in 2011), the NIH and the National Science Foundation. Yet there is scant evidence indicating how to do this in practice. On a methodological level, we are—to the best of our knowledge—the first to bring field experimental methods to a workplace setting where the participants are engaged in scientific knowledge production. Evidence from randomized experiments on the scientific community such as ours will presumably be increasingly valuable to policymakers as they consider reforms to scientific institutions (Azoulay, 2012), and more generally our study provides a template for the design of randomized control trials in innovation research (Boudreau & Lakhani, 2016). We show that creating settings where scientists meet face-to-face to discuss early-stage research ideas can be useful for fostering

collaboration. However, time spent in such "mixer" events has opportunity costs, and we thus remain agnostic on the effect of such activities on scientific productivity and on welfare more generally.

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