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To Stem the Tide: Organizational Climate and the Locus of Knowledge Transfer

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Abstract. Prior work has maintained that organizations benefit from managing the transfer of proprietary knowledge. Transfer is often advantageous *within* organizational boundaries but may be harmful *across* them, because it might erode competitive advantage. Hence, we ask: How can organizations affect the direction in which knowledge flows? We examine the role of organizational climate as a governing mechanism for knowledge transfer. Our empirical strategy consists of a mixed-methods approach leveraging qualitative and experimental data over two cycles of theory building and theory testing. We start with an extensive field study of the European Organization for Nuclear Research (CERN), leveraging the insights from desk research, field observations, 53 interviews, and a laboratory-in-the-field experiment involving 518 physicists. We then provide a causal test of the emerging framework by means of two laboratory experiments with 389 participants. Our findings suggest employees are more likely to transfer knowledge to their colleagues when they identify as an integral part of the organization, but they would rather transfer knowledge to outside competitors when their organization encourages them to outperform coworkers. In the presence of an organizational climate that is unfavorable to preventing knowledge spillovers, we argue, organizations can redirect the locus of knowledge transfer internally by acting upon an individual employee's job design and socialization regime.

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Introduction

Prior work has maintained that organizations benefit from managing the transfer of proprietary knowledge (Hansen 1999, Argote and Ingram 2000, Evans et al. 2015). In particular, it has been argued that organizations should facilitate the free flow of knowledge *within* their boundaries (Szulanski 1996, Levine and Prietula 2012, Pierce 2012, Tortoriello et al. 2012, Argote and Fahrenkopf 2016) but exert some caution in governing the flow of knowledge *across* them (Zander and Kogut 1995; Tsai 2001, 2002). When interacting with members of other organizations, employees can in fact generate knowledge spillovers (Singh 2005, Shipilov et al. 2017), which have the potential to erode competitive advantage and threaten the very survival of an organization (Faems et al. 2008, Jarvenpaa and Majchrzak 2016).

How might organizations govern *the locus* of knowledge transfer—that is, *where* employees transfer organizational knowledge? Can they enrich the organizational knowledge stock by motivating employees to transfer knowledge to their colleagues (Darr et al. 1995, Baum and Ingram 1998, Argote et al. 2003, Jain 2013) while at the same time dissuading them from transferring knowledge to competitors (Almeida and Kogut 1999, Song et al. 2003, Singh 2005)? Previous literature has answered this question by focusing on the role of formal mechanisms, such as legal and financial incentives (Agarwal et al. 2009, Gambardella et al. 2015). However, in line with a more elaborated view of human motivations (Obloj and Sengul 2012, Gubler et al. 2016), recent work has expanded the inquiry to *informal* mechanisms, which act on individuals' intrinsic drive to behave in accordance with the goals of the organization they belong to.

A notable example comes from Flammer and Kacperczyk (2019), who found that employees were less likely to disclose organizational knowledge after they departed from organizations engaged more highly in corporate social responsibility. In this paper, we follow their precedent by examining the role of additional informal levers firms can act upon to govern the locus of knowledge transfer. In particular, we focus on features of the organizational climate, and argue that employees will be (a) more likely to transfer knowledge *within* organizational boundaries when they feel to be an integral part of the organization (high *organizational identification*; Foreman and Whetten 2002, Schilke 2018) and (b) more likely to transfer knowledge *across* organizational boundaries when the organization encourages them to outperform coworkers (high *performance climate*; Alexander and Van Knippenberg 2014, Černe et al. 2014). We further argue that, when the organizational climate is unfavorable to preventing knowledge spillovers, organizations can redirect the locus of knowledge transfer internally by acting on an individual employee's job design and socialization regime (Gottschalg and Zollo 2007). The use of these organizational and individual levers contributes to better align the goals of the individual to those of the organization, and, as per our title, stem the tide of knowledge spilling across a firm's boundaries.

Our claims are based on an extensive field study of the European Organization for Nuclear Research (CERN), operator of the largest particle physics laboratory in the world. CERN scientists are organized in seven large research teams (called experiments or collaborations) all using the Large Hadron Collider (LHC), the world's largest and most powerful particle collider (Knorr-Cetina 1995, Tuertscher et al. 2014). The seven experiments differ along many dimensions, including size (between ~100 and ~3,000 affiliated scientists) and the type of physics studied (e.g., cosmic rays from particles collisions, standard model, heavy ions). Our analysis focuses on ATLAS and CMS, the two largest, general-purpose experiments, which were created to be in competition with one another to ensure the validity of scientific discoveries through independent replication. In this context, knowledge transfer across organizational boundaries is quite dangerous: if knowledge flows from one experiment to the other, independence is compromised, and claims of priority are in jeopardy, along with access to human and financial resources. These features bring center stage the need to prevent employees from acting as conduits for knowledge spillovers.[1]

Our empirical strategy consists of a mixed-methods approach (Edmondson and McManus 2007, Guler 2007) combining theory development from field data with an experimental test of the emerging theory, as illustrated by Fine and Elsbach (2000) and implemented by, among others, Huang and Pearce (2015) and Slade Shantz et al. (2020). In particular, we start by developing a theory about the influence of organizational climate on the locus of knowledge transfer in organizations. To this end, we triangulate qualitative data from interviews and field observations conducted at CERN with extant theory. Next, we conduct a within-subject laboratory-in-the-field study involving physicists affiliated with ATLAS and CMS, with the aim to empirically document differences in their intention to transfer knowledge within/across organizational boundaries. The results of this study provide preliminary evidence of substantial differences in features of the organizational climate characterizing the two organizations. We next go back to the field and triangulate our intuition about the role of two specific features of organizational climate (i.e., organizational identification and performance climate) with members of the two organizations. Finally, we design and conduct two laboratory experiments where we manipulate organizational identification and performance climate independently and observe their effects on the locus of knowledge transfer.

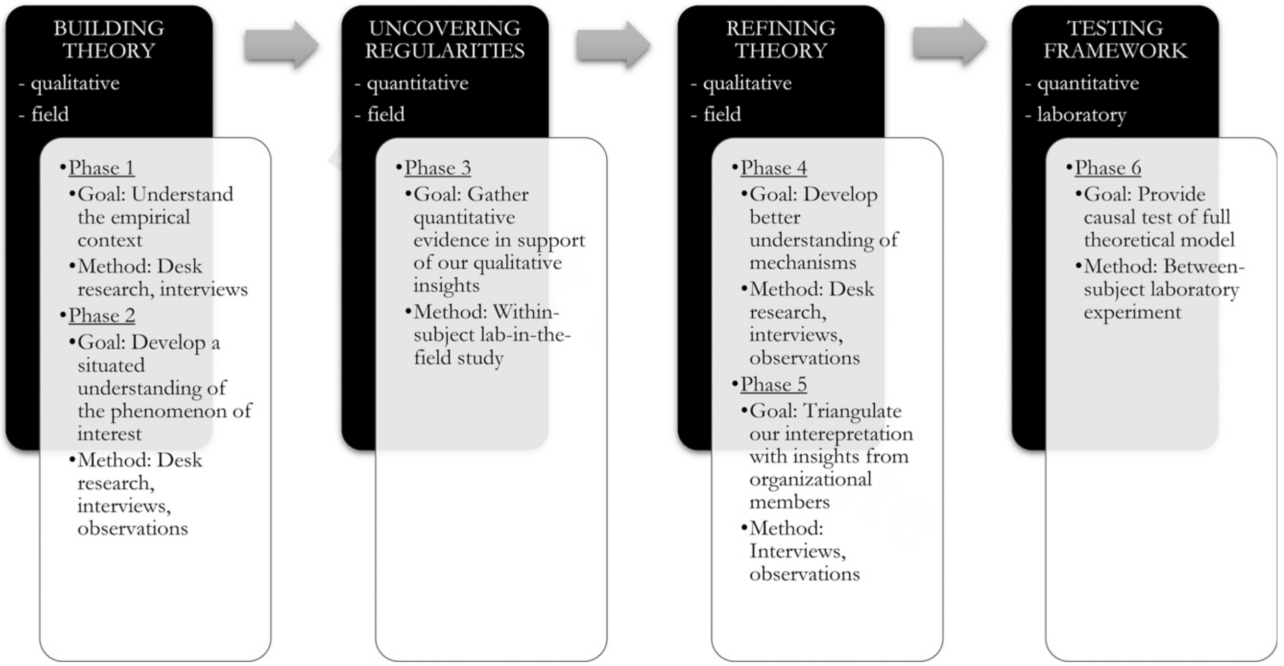
From a theoretical standpoint, we believe our study makes a number of important contributions. For the literature on organizational learning (Argote and Ingram 2000, Levine and Prietula 2012), we speak to the tension between intra- and inter-organizational knowledge transfer by emphasizing how different features of organizational climate can influence the locus of knowledge transfer. In contrast with the predominant focus on legal barriers and financial incentives (Agarwal et al. 2009, Gambardella et al. 2015), we highlight how firms can defend against knowledge spillovers by intervening on the fabric of their organizations. For literature on interest alignment (Gottschalg and Zollo 2007, Mahoney et al. 2009), we show how organizations can motivate their members to behave in line with organizational goals by acting on a variety of different levers, both at the organizational level (i.e., organizational climate) and individual level (i.e., job design and socialization regime). Finally, by explaining individual behavior as the result of both firm- and individual-level characteristics, we contribute to the emerging literature on the complex interplay between micro and macro levels of analysis (Felin et al. 2015, Lee et al. 2016). Previous studies have tended to explain the choice to transfer knowledge by focusing on variance either across individuals, independent of their organizational affiliation (Argote et al. 2000, Cabrera and Cabrera 2002), or across organizations, holding intra-organizational variance constant (Lawson et al. 2009, Jarvenpaa and Majchrzak 2016). An important exception is the multilevel model developed by Levine and Prietula (2012) to show how knowledge transfer impacts organizational performance. This paper follows their lead by exploring both inter- and intra-organizational variance. Our results suggest that some characteristics at the individual level can compensate for unfavorable organizational factors.

From a methodological standpoint, we believe our study offers two contributions to the emerging stream of experimental work in organizational theory and strategic management (Bitektine et al. 2018, Di Stefano and Gutierrez 2019). First, our work provides an example of how to integrate qualitative examination and experimental data through cycles aimed at theory building and theory testing (Fine and Elsbach 2000). As originally argued by Cialdini (1980, p. 44), one can avoid the criticism that experimental research is "artificial and epiphenomenal" by adopting a full-cycle approach to research, which alternates between theory building from qualitative data and theory testing by means of experimental data. Our approach consists of two of such iterations over six phases of data collection, leveraging the insights from desk research, field observations, 53 interviews with CERN physicists, a laboratory-in-the-field study of 518 physicists affiliated with ATLAS and CMS, and two laboratory experiments with 389 participants. This approach allows us to generate a situated understanding of how differences in organizational climate impact the locus of knowledge transfer, and to develop a theoretical model that we later test through experimental data (Fielding and Fielding 1986). Second, our work provides an example of how to use experiments to study the effects of an organizational trait that has proven difficult to pin down in the field (Weber and Camerer 2003). To provide a causal test of the effect of organizational climate on knowledge transfer, one would want to manipulate the former and observe how the latter changes as a result. This would be feasible in the laboratory, but at the expense of external validity (Angrist and Pischke 2010). In contrast, it may not be feasible or realistic to manipulate inherent organizational traits in the field (Harrison and List 2004). Thus, neither a laboratory experiment nor a field experiment, alone, would be able to fully test our theory, and neither, alone, would strike the appropriate balance between rigor and relevance (Vermeulen 2005). We endeavor to solve this problem of testimony (King et al. 2021)—in which no single empirical study provides a sufficient basis for inference (Berchicci and King 2022)—by leveraging the complementarities among different methods, in the spirit of consilience (Wilson 1998). In particular, we use the laboratory-in-the-field to document how members of different organizations think about the locus of knowledge transfer "in the wild" (Di Stefano et al. 2015, p. 907). We leverage the laboratory experiments to provide causal evidence of the underlying mechanisms, generalize their role beyond the specific context of our field study, and examine actual instead of intended behavior.

Study Overview

Our empirical strategy consists of a mixed-methods approach combining two iterations between theory

Figure 1. Study Structure



Notes. Our empirical strategy consists of a mixed-methods approach combining two iterations between theory building and theory testing over six phases of data collection. The figure provides a graphical overview of the overall structure of the study.

Table 1. Overview of Study Phases

Phase	Time	Data	Brief description	Main purpose of data collection
Phase 1	January–March 2016	Desk research	CERN website and press releases; Academic literature discussing CERN; Books and monographs on the history and achievements of CERN	Gain familiarity with the context of CERN and scientific collaboration more in general
	January–October 2016	Interviews	Eleven interviews with: eight physicists working at LHC (ATLAS, CMS, LHCb, TOTEM), two theoretical physicists (not affiliated with any experiment), and one physicist affiliated with an experiment outside LHC	Develop an overall understanding of knowledge flows across experiments at CERN
Phase 2	January–March 2017	Desk research	Re-examination of sources previously consulted with a more specific focus on ATLAS and CMS	Become knowledgeable about the history and specificities of ATLAS and CMS
	September 2017–February 2018	Interviews	Thirteen interviews with 10 informants from ATLAS and CMS. We interviewed one of the spokespersons from ATLAS and the two spokespersons from CMS twice, at the beginning and at the end of this round of data collection	Understand along which dimensions ATLAS and CMS differ, and with what effect on the tendency of their members to transfer organizational knowledge within vs. across organizational boundaries
	February 2018	Observations	Two days at CERN, accompanying informants during their workday, and observing interactions in offices, cafeteria, etc.	Gather observational data to help the development of our situated understanding
Phase 3	February–April 2018	Laboratory-in-the-field	Laboratory-in-the-field administered through a survey to members of ATLAS and CMS, for a total of 518 respondents	Gather empirical evidence of differences in intended locus of knowledge transfer across ATLAS and CMS
Phase 4	April 2018	Desk research	Fifty-seven comments sent at the end of the experiment and 11 emails exchanges with participants from ATLAS and CMS	Understand the motives and reactions of our participants
	May 2018	Observations	Two days at CERN, meeting with representatives from ATLAS and CMS, and participating in their activities	Debrief with participants and management
	May–June 2018	Interviews	Thirteen interviews with 10 new informants, as well as 3 former informants from ATLAS and CMS	Develop potential interpretations of results
Phase 5	March 2020	Observations	Presented findings from the paper in an online meeting open to members of both organizations and attended by about 50 participants	Provide an overview of the study and its main results, and discuss our interpretation of results with members of both organizations
	April–June 2020	Interviews	Sixteen interviews with 16 new informants from ATLAS and CMS	Triangulate our interpretation of results with members of the two organizations
Phase 6	July 2020	Laboratory experiments	Two laboratory experiments administered online to a total of 389 participants recruited through Prolific	Provide causal test of the emerging framework, generalize beyond the field context, uncover differences in behavior (rather than intentions)

Notes. Our empirical strategy consists of a mixed-methods approach combining two iterations between theory building and theory testing over six phases of data collection. The table provides detailed information about each of the six phases around which our data collection was organized.

building and theory testing (Cialdini 1980, Fine and Elsbach 2000) over six phases of data collection, as illustrated in Figure 1 and detailed in Table 1. We started building theory from qualitative data with the aim to identify which of the many dimensions that characterize an organizational climate can affect the locus of knowledge transfer. To this end, in *Phase 1* (2016), we completed extensive desk research and conducted a first round of interviews with members of different experiments at CERN, whereas in *Phase 2* (2017) we focused our attention on ATLAS and CMS and conducted a second round of interviews with members of the two organizations. Once we formed a preliminary understanding of how differences across the two organizations could be linked to the intention to transfer knowledge, we decided to gather quantitative evidence in support of our qualitative insights. Toward this goal, in *Phase 3* (2018), we designed a within-subject laboratory-in-the-field study, which we administered to all scientists affiliated with ATLAS and CMS. Next, we circled back to our theory to make sense of the empirical evidence generated by our laboratory-in-the-field. In *Phase 4* (2018), we collected feedback about the study and completed an additional round of interviews. Once we had a working paper to circulate, in *Phase 5* (2020), we shared our insights in a joint presentation to ATLAS and CMS and conducted a final round of interviews with members of both organizations. We concluded with *Phase 6* (2020), when we designed and conducted two laboratory experiments aimed at testing the full theoretical model that had emerged from the field. Moving to the laboratory allowed us to isolate the relationships of interest and provide a causal test of the effect of organizational climate on the locus of knowledge transfer. The internal validity of the experiments complements the external validity of the field study and allows us to provide evidence in support of our claim that firms can influence the locus of knowledge transfer by acting on distinct features of their organizational climate. For ease of reading, we group our six phases based on whether they were aimed at theory building or theory testing and present the empirical details and main findings accordingly.[2]

Phase 1 and Phase 2: Building Theory (2016–2017)

Our field study at CERN started with two rounds of qualitative data collection. We entered the field in early 2016 first using desk research, followed by interviews, to get familiar with the context and develop a situated understanding of knowledge flows among scientists in different experiments. We used the insights generated from this first phase of data collection to refine our empirical strategy and, most importantly, narrow our focus to two organizations, ATLAS and CMS, within the broader context of LHC experiments at CERN. The second phase of data collection produced detailed information about these two organizations gleaned first from focused desk research, and then from interviews and on-site observations. By the end of 2017, we believed we had developed a good understanding of how knowledge travels within/across organizational boundaries in our empirical context. We were also able to connect insights from qualitative examination to extant theory, thus allowing us to triangulate our intuitions. The outcome of this iterative process was the conjecture that organizational climate affects an employee's propensity to transfer organizational knowledge within/across organizational boundaries.

Phase 1

In the earliest stages of this phase, we conducted extensive desk research, combining several sources. We used CERN's website (https://home.cern/science) and press releases (https://home.cern/press) to better understand how the institution is organized and the activities it conducts. Next, we read contributions regarding CERN in the fields of management, sociology, and philosophy of science. Finally, we examined books and monographs discussing the history and achievements of CERN over time.

Once we had familiarized ourselves with the context, we entered the field and conducted a first round of 11 exploratory interviews with CERN scientists. Specifically, we interviewed the following: (a) eight physicists working for five different LHC experiments (ALICE, ATLAS, CMS, LHCb, and TOTEM); (b) two theoretical physicists working at CERN but not officially affiliated with any experiment; and (c) one physicist working at an experiment using a different detector but relying on CERN for some of its analyses. We selected our informants using a mix of theoretical sampling (by contacting the spokespersons for the different experiments and prominent theoretical physicists) and snowballing (by asking former interviewees to suggest who we should interview next). Interviews were conducted by one or both coauthors, lasted between 35 and 70 minutes each, and were mainly held by phone or video conference. All interviews were recorded and transcribed, for a total of 387 minutes of recording and 152 single-spaced pages of transcripts.[3] We took detailed notes during interviews, for a total of 21 pages, which we analyzed together with the transcripts. Although both coauthors were outsiders to the organization, one had a close acquaintance working at one CERN experiment. We asked this qualified informant to act as a sounding board for ideas and observations we developed along the way. By the end of this process, we had developed a good understanding of knowledge flows across CERN experiments.

Main Insights. CERN is a leading institution, operating the world's largest and most powerful particle collider, named LHC (Knorr-Cetina 1995, Tuertscher et al. 2014). The project for building LHC was launched in the 1990s and completed in 2008, with operations beginning November 20, 2009. The collider successfully operated for a first run in the period 2009–2013, leading to the discovery of, among others, the Higgs Boson particle in July 2012.[4] After a two-year shutdown for an upgrade, a second operational run was conducted in the period 2015–2018 with considerable improvements on luminosity and therefore an increased number of collisions. CERN brings together more than 12,200 scientists of 110 nationalities and groups them in large research teams that each use the LHC for their analyses. The experiments active in our study period were ATLAS, CMS, LHCb, ALICE, LHCf, TOTEM, and MoEDAL, while an eighth experiment, FASER, was approved to become operational after we concluded our study.

Among these experiments, we found ATLAS and CMS to be particularly suitable for our research interests. Although both housed at CERN, they were established as two separate organizations with the same scientific goals (Boisot et al. 2011).[5] This design choice was made to ensure that each organization would compete with, and be checked by, the other, such that if one makes a discovery, the other should be able to verify it before the discovery is announced publicly. Despite sharing institutional linkages (through CERN), using the same key resource (LHC), and having their headquarters physically colocated (in Geneva, Switzerland), each organization has a strong incentive to be the first to make any discovery to secure recognition, research funds, and human resources. This tension between competition and collaboration emerged clearly during the first phase of our data collection. It has also been described in previous literature (Boisot et al. 2011) and openly reported in official CERN documents, as shown by this post on CERN's website for the 25th "birthday" of ATLAS and CMS[6]:

> ATLAS and CMS are like close sisters, the best of friends and competitors all at once. Today they are both celebrating their 25th birthdays. On 1 October 1992, the two collaborations each submitted a letter of intent for the construction of a detector to be installed at the proposed Large Hadron Collider. These two documents, each around one hundred pages long, are considered the birth certificates of the two general-purpose experiments.

The coexistence of competition and collaboration was also clearly reflected in the way our informants talked about the two organizations, as in the case of this CMS physicist:

> I work at one experiment at CERN, which relies on LHC, the accelerator that is at CERN. I work at this experiment called CMS. Basically, there is another experiment called ATLAS, which studies more or less the same things as CMS. Well, they are, if you want, in direct competition, and they work more or less on the same things.—Informant 1

One notable aspect that emerged during this first round of interviews was the difference in attitude between informants from ATLAS and informants from CMS. When talking with our two CMS informants, we noticed that they tended to communicate their individual perspective, or that of the research team they worked with, with an emphasis on competition. Meanwhile, our two ATLAS informants referred most often to the goals of their organization and downplayed competition. In the quote below, an ATLAS informant explains that scientific advancements are led by the need to create a shared language in the organization, so that scientists can leverage it to collaborate:

> It's not competition. It's like—how do you say?—setting a standard. So, you say: to obtain this specific measurement, you need this specific 'ingredient' and then you need to follow this specific methodology and present the results in this specific way. You should be able to give this information to others so that they can reproduce the result.—Informant 5

ATLAS scientists seemed to have a positive opinion of their working environment. For instance, the quote below shows that all ATLAS scientists get the chance to present at conferences, based on a rotation system. Note the use of the pronoun "we" as opposed to the "I" used by our previous CMS informant:

> At ATLAS, we have a committee assigning presentations based on a rotation system. Since we are more than 3,000, we try to alternate. This allows everybody to do at least one or two presentations every three or four years. But this also means that you might have to present stuff that was done by someone else in the experiment.—Informant 3

We also observed differences in the expressed adherence to formal organizational rules. For instance, when we asked if there were written rules governing the flow of proprietary knowledge among members of CERN, an informant from ATLAS immediately mentioned:

> Well, yes, we have them. For instance, if I am not mistaken, the official policy says that, when we find something that could be a discovery, we tell the other experiment one week in advance with respect to the moment when the announcement is planned. One week is not enough to start the analysis from scratch. But if the analyses of the other experiment are advanced enough, the policy allows to have a result that

> confirms or disconfirms the one of the other experiment.—Informant 5

Similar observations were shared by informants from other CERN experiments (e.g., Informant 10), as well as by a theoretical physicist who was working at CERN but not affiliated with any experiment, who explained: "Both ATLAS and CMS have quite strict rules about which members of the collaborations co-author papers, and which use of information might be construed as insider information" (Informant 9). Our CMS informants, meanwhile, seemed to ignore the existence of rules governing knowledge transfer:

> Well, I don't know. I believe that, a couple of times when someone disclosed some information, our bosses wrote an email with some guidelines telling people what to share and not to share. But well, these rules are not really codified. There are some guidelines, but it's not something like 'if you do something, you get punished.' Everything is left to self-management.—Informant 1

Phase 2

Our first encounters with members from ATLAS and CMS sparked our curiosity about the extent to which, despite looking very similar on paper, these organizations might be fundamentally different. We hence devoted Phase 2 of our data collection to developing a better understanding of the dimensions along which the two organizations differed, as well as how those differences might influence the locus of knowledge transfer by employees. To this end, we set out to establish contact with the spokespersons of the two organizations, which proved particularly time-consuming. In the meantime, we reviewed our previously collected materials in an iterative fashion to prepare ourselves for the new wave of data collection. We finally got access to the spokespersons at the end of summer 2017. Each organization had two spokespersons and we interviewed all four. Next, using a mix of theoretical sampling and snowballing, we gradually involved other informants, for a total of 13 additional interviews, including five informants from ATLAS and five from CMS. Interviews lasted between 30 and 90 minutes and were held face-to-face in the presence of both coauthors. Unfortunately, most of our informants in this stage were not comfortable being recorded during the interviews. In these cases, we took notes and transcribed the key points made by each informant immediately following their interview, generating 11 pages of notes in total. In the two cases where interviews were recorded, conversations generated 63 minutes of recording and 20 single-spaced pages of transcripts. Finally, we spent two days at CERN in Geneva (Switzerland) to visit LHC, engage with our informants during their workday, observe interactions in the offices, as well as over lunch breaks, and hang out with them after work. During the two days spent at CERN, we collected 13 pages of field notes. Although the absence of interview transcripts substantially limited our ability to analyze interview data through an iterative content-analysis process (Glaser and Strauss 1967, Miles and Huberman 1994), we tried to replicate a similar process with interview notes (see online appendix). By the beginning of 2018, we believed we had a good understanding of how ATLAS and CMS differed, and how those differences effected the tendency of their members to transfer proprietary knowledge within/across organizational boundaries. We were also able to link our understanding to findings from prior research (Locke 2001).

Main Insights. As soon as we started to get acquainted with ATLAS and CMS members, we realized our intuition about differences between their organizations had some merit. As one informant from ATLAS put it (Informant 19), the two experiments have different "genetic traits." Members of the two organizations continuously hinted at the differences while discussing their relationship with employees of the other organization. For instance, one ATLAS informant explained to us that the two experiments are seen as "twin sisters" with "differences" and "interdependencies" (Informant 12). When asked to characterize the personalities of the two organizations, this informant described ATLAS as "calm" and "rigorous" and CMS as "pushy" and "aggressive." Similarly, another ATLAS informant (Informant 13) described ATLAS as "less organized" but "stricter and a perfectionist," and described CMS as "more top-down and efficient" but with a tendency for "risk-taking" and "laissez-faire" when it came to potential discoveries. Another interviewee (Informant 19) further insisted on the idea of ATLAS leadership being more "democratic" and oriented toward "consensus," to the point of being criticized by some for being "not as strong." Differences between the two experiments were also emphasized by our CMS informants:

> Well, it's clear that each collaboration [ATLAS and CMS] has its own history and its way of being, which are quite different. For instance, with respect to the extent to which the spokesperson has power, what are the procedures for approving publications and so on.—Informant 14

When asked about the origins of these differences, informants mentioned various factors, such as the presence of different national cultures, the choice to emphasize some values instead of others, or the complex interplay between structures, routines, and operations. However, independent of how they were generated, we saw, felt, and heard about these differences in each interview. The juxtaposition between the two organizations became very visible once we visited headquarters, as explained in Figure 2.

The divide that materialized physically in the workspace design was also tangible when talking to members of the two organizations. A first relevant dimension along which we observed differences in the two experiments was in the extent to which members identified with their organization. Employees at ATLAS had a strong tendency to adopt the point of view of the organization as a whole, and explicitly referred to being part of a group any time we asked questions about their choices as individuals. For instance, one informant described the process leading to the publication of results as a collective one, in which individual scientists act for the collective goals of the organization:

> You have a problem that you might easily solve alone in your room, but still you sit with others and try to solve it collectively. In this way, everyone can give their contribution. You write a lot of collective reports that then lead you to the final result. Probably, you could have solved the problem in less time by working alone but, by sharing with others, you create common practices and hope that others will do the same in the future.—Informant 5

In contrast, CMS employees seemed much more self-serving. The quote here, taken from an email exchange with a CMS informant, exemplifies the tendency to adopt an individualistic perspective:

> At a researcher level, the aim is to have better results (earlier/more precise/more complete) compared to the other experiment. This can help you when applying for academic positions later in your career. Put it differently: the existence of a competitor, with similar capabilities and working on an almost identical scientific program, sets a benchmark and, for you to gain credibility as a researcher, you can't allow your results to be too far from that benchmark.—Informant 17

Given the tendency we had started to identify, it was not surprising to hear a more senior informant at CMS explicitly characterizing the lack of organizational identification as an "issue" with junior scientists:

> The identification with the experiment was much stronger 20 years ago compared to now. The feeling of 'being a family' was stronger, since we were only a few people and we knew each other well. Now, the experiment is so big that, especially for young people who are new to it, that aspect of identification is lower and experienced in a completely different way with respect to how we experienced it back then.—Informant 13

Figure 2. (Color online) ATLAS and CMS Headquarters, Building 40

Notes. The main offices of ATLAS and CMS are colocated in Building 40. Hosting more than 300 offices, this building is composed of four towers: ATLAS offices are located in two adjacent towers (C and D), right across from the towers housing CMS (A and B). Towers are connected at the ground floor level, where employees gather to buy food from the cafeteria and sit at tables that are split equally between the two sides of the building.

Another relevant dimension along which ATLAS and CMS seemed to differ was in the extent to which members reported feeling in competition with their colleagues. ATLAS employees like the one below described a collaborative culture, where competition is not as strong as one could imagine:

> On paper it looks like there is a 'culture of fear', as in a cold war, where you always have to be in competition with others. But, in reality, there is no competition. This whole idea of competition is a bit weird to us.—Informant 3

Overall, CMS scientists seemed much more aware of the boundaries between colleagues, and of being in competition with their peers. For instance, one of them recalled a potential discovery that had emerged a few months before we spoke (and was not confirmed later), and explained that they would have never "dared" to talk about it even with a peer they worked closely with: "If this potential bump in the data was in the analysis of the colleague working next to me in the office, I would have never dared to ask them something about it, you see?" (Informant 4). Another informant pushed the argument further, asserting that their experiment (CMS) needed to keep up with, if not outperform, the other (ATLAS):

> ATLAS and CMS are the only experiments in the world that can pursue and achieve the physics results they are producing. This means that being ahead of your competitor automatically makes you the best in the world. […] I think that what would create considerable damage to an experiment would be to become known as the 'second best' experiment at CERN. This negative image, in the long run would affect the power of the experiment to attract funding.—Informant 17

A final notable difference between the two organizations emerged when talking about managing organizational knowledge. The spokespersons of both organizations explained that no information about potential discoveries should be shared, under any condition, with members of the competing organization. The rationale is to avoid creating any possible bias that may invalidate results, while also preventing opportunities for the other organization to exploit proprietary insights. A CMS informant explained:

> It is all based on the professional honesty of scientists working at the analysis. It is in our own interest that there are no knowledge leakages. We want to make sure that the analyses of the two experiments are independent, because only then one experiment can confirm the results of the other. If there is an interaction between the two experiments, the risk is that they both start taking the same research avenue, because they talked to each other. So, it is in our own interest that knowledge leakages are minimal, in order to guarantee the quality of our work.—Informant 14

Members of ATLAS seemed to share this vision and were adamant in stating that organizational knowledge should not be transferred to members of the other organization before priority is clarified:

> My friends who are theoretical physicists send me emails, messages in the internal chat, and so on, but I don't answer. If they contact me, it means that the situation is already critical, because it means that they might already know about potential new discoveries we are working on. The thing is: if the other experiment is seeing something in the data and I become aware of it, then I might be biased. Specifically, I could "suddenly" see the same thing in the data, or try to find it, look for it. Not with a malevolent intention, but just because I have been triggered by the other experiment. And this is not the best scientific method to have an independent confirmation of results.—Informant 5

This strict adherence to rules was sometimes described as an impediment to information flows that could have benefited the organization, as explained by this ATLAS informant recalling a specific episode:

> We had to grant access to the internal data at the basis of one analysis to one of our theoretical physicists in [an Italian city hosting a national laboratory of physics]. The bureaucracy at ATLAS was so burdensome that, if one was to follow all the procedures, the access would have been granted after the analysis was published. So, we simply decided not to grant access, as it would have been useless.—Informant 3

In contrast, CMS informants tended to question the rationale behind the norm, even joking about organizational reminders not to transfer sensitive information to the competing organization: "At the start of each meeting, there was this precautionary dressing-down of the spokesperson, who used to say: Please remember that what I am about to tell you will remain here; and please remember that you are not supposed to discuss this with your besties at ATLAS" (Informant 4). Others emphasized how interorganizational knowledge transfer, despite being harmful to the organization, could lead to personal returns for the individual. Here we report a conversation between two CMS informants, recalling a case where a scientist's individual goals conflicted with those of the organization:

> Informant 14: A physicist can also decide to focus on things that will bring personal returns for his career.
>
> Informant 13: Yes, for example, some time ago, someone within the experiment knew about a result that was about to be published. He collaborated with some theoretical physicists and, as soon as that result was

> out, he published another paper on his own, together with these theoretical physicists. This is not okay, because he had the advantage of knowing about the result before others. He exploited a specific situation.

Of course, we also noticed some commonalities across the two organizations. For instance, when pushed to further articulate what drove the choice to transfer proprietary knowledge to a colleague, most of our informants tended to agree that knowledge transfers more easily when they can trust the colleague, either because they know them "personally, as in the case of someone you have worked with before" (Informant 15), or because they are highly reputed:

> Two full professors from the two experiments who know each other and trust each other will share knowledge. But if some random person from ATLAS goes to a full professor at CMS, or vice-versa, they will never get the information they are looking for.—Informant 3

Similarly, informants reported being more willing to transfer knowledge that is not of strategic importance to the organization. For instance, one informant at ATLAS (Informant 12) explained that sharing information that is not "hot" is not problematic and might actually help with cross-checking preliminary results. Another ATLAS informant summarized this point effectively in the following quote:

> Well, there might be two typologies of knowledge sharing: technical information, for example information about some tools that we use. People from the other experiment might want the code behind them, so that they can use the same one. This is not problematic. Well, let's say that there is no copyright on this type of information, I believe. So, it can be shared via email or during a coffee break without problems. Then you have sharing of knowledge concerning physics results. This information should be shared only at the managerial level but, even at lower levels, we often exchange comments on results that are about to be published. So, we often know the results that the other experiment is about to present. However, sharing this kind of information is different. Let's put it this way: if you share, you don't want your name mentioned as a source.—Informant 3

Discussion

Our qualitative investigation revealed interesting differences between ATLAS and CMS. In particular, we observed that ATLAS informants seemed to identify more with the organization and displayed a stronger tendency to keep proprietary knowledge within organizational boundaries. At CMS, on the other hand, we noticed our informants felt more in competition with one another and reported a higher propensity to transfer knowledge to members of the competing organization.

Extant literature seems to support our intuition that these different features of the organizational climate might have a role in explaining differences with respect to the locus of knowledge transfer. According to our qualitative examination, a first driver behind the choice to keep knowledge within organizational boundaries, or to let it flow across them, may be related to identifying with the organization to which one belongs. We connect this to organizational identification, defined as the extent to which members of an organization perceive themselves as an integral part of it (Ashforth and Mael 1989, Mael and Ashforth 1992). Previous literature discusses the role of organizational identification in increasing job and organizational satisfaction (Van Dick et al. 2004), as well as organizational commitment and loyalty (Adler and Adler 1988, Foreman and Whetten 2002), thus reducing turnover (O'Reilly and Chatman 1986, Conroy et al. 2017) and positively contributing to the success of an organization (Pratt 1998, Jones and Volpe 2011). Organizational identification has also been shown to shield organizational members from environmental pressures by increasing certainty and focusing attention (Schilke 2018). Results from our qualitative investigation suggested that organizational identification might also lead organizational members to prefer transferring knowledge within, rather than across, organizational boundaries.

Another factor in our qualitative investigation that emerged as potentially relevant for the locus of knowledge transfer is related to the feeling of being in competition with coworkers. We connect this to motivational climate, which refers to how members of an organization perceive organizational practices to evaluate them and determine success or failure (Černe et al. 2014). This construct is related to goal orientation theory (Dweck 1986) and the distinction between mastery (Van Yperen and Janssen 2002) orientation, where there is a "focus on task mastery, [and] success is understood in terms of learning," and performance orientation, which "entails wanting to do well compared with others or with normative standards" (Alexander and Van Knippenberg 2014, p. 426). At the organizational level, scholars have made the distinction between a motivational climate oriented toward mastery, which "supports effort and cooperation, and […] emphasizes learning, mastery, and skill development," and a motivational climate oriented toward performance, where "normative ability, social comparison, and intrateam competition are emphasized" (Černe et al. 2014, p. 175). According to Černe and colleagues (2014), some features of the motivational climate can moderate the relationship between a lack of knowledge transfer among colleagues and creativity.

Our qualitative examination further suggests that they also directly affect the locus of knowledge transfer. In particular, we observed that colleagues in a motivational climate oriented toward performance—a *performance climate* as per Černe et al. (2014)—preferred transferring knowledge to colleagues in a different organization rather than to colleagues in their own organization, whom they considered direct competitors. This is in line with recent work by Zhu et al. (2019), which argues that performance climate can bring forth a tendency to hide knowledge from others.

Results from our qualitative investigation also suggested that differences between ATLAS and CMS dissolved when talking to individuals in positions of responsibility, as all the spokespersons with whom we interacted mentioned strict and explicit rules about knowledge transfer. This intuition is consistent with research by Gottschalg and Zollo (2007), according to which job design (in our context, holding a position of responsibility) influences the extent to which employees behave in line with organizational goals, creating a lever that organizations can use to enhance interest alignment. According to the authors, another relevant lever that organizations can act on is an employee's socialization regime. This led us to speculate that members of CMS who are based in the headquarters should display a preference for transferring knowledge within, rather than across, the boundaries of their organization, since the possibility to socialize on a regular basis with their coworkers could transform them from 'competitors' into 'colleagues.' Finally, an observation common to members of both experiments was that knowledge transfers more easily when: (a) when they trust the colleague, either because they know them directly, or because they are highly reputed; or (b) the knowledge involved is not of strategic importance to the organization. This resonates with research showing that the perceived threat of expropriation is lower with trustworthy counterparts (Bradach and Eccles 1989, Dyer and Nobeoka 2000, Kale et al. 2000) and less valuable knowledge (Liebeskind 1997, Hernandez et al. 2015, Wadhwa et al. 2017).

Phase 3: Uncovering Empirical Regularities (2018)

We next leveraged the insights generated during the first two phases of our field study to design and execute a laboratory-in-the-field study. The main goal of this data collection was to provide systematic evidence of the differences previously identified through qualitative investigation. The study was administered by means of a survey distributed to all scientists affiliated with ATLAS and CMS. In this survey, we gave participants a vignette describing another scientist with whom they might interact. The vignette was followed by a series of questions aimed at capturing the likelihood of knowledge flowing between the participant and the colleague whose characteristics we manipulated in the vignette. We assigned two vignettes per participant and randomized their assignment, facilitating within-participant comparisons.

We chose a vignette study because of the nature of the behavior we were interested in examining. Our dependent variable is the locus of knowledge transfer—that is, the propensity of an employee to transfer a firm's proprietary knowledge within/across organizational boundaries. We anticipated at least two problems with observing this variable directly. First, as our participants admitted, most of these exchanges happen in informal situations ("I am quite careful. As long as they [scientists from the other experiment] write emails or messages that's easy, I can avoid answering. The problem is when they ask you questions over coffee," said Informant 5). Observing these situations directly would have been impossible. Prior research has suggested that vignettes are particularly useful in cases where the behavior of interest is difficult to observe (Di Stefano and Gutierrez 2019). Second, transferring knowledge across firm boundaries is a sanctionable norm violation. This raised an ethical issue: making knowledge transfer more visible would have the de facto effect of increasing the likelihood of detecting (and sanctioning) it. Given these constraints, we concluded that vignettes were an ideal vehicle for our laboratory-in-the-field study.

We next discuss key design choices, main analyses, and general conclusions that we can draw from the study. We report additional details on each of these elements in the online appendix.

Design

We administered our vignette in a survey that we developed and pretested through a series of iterations with members of ATLAS and CMS. On Monday, February 26, 2018, the secretariat of ATLAS distributed the survey through an email targeting all 2,777 physicists affiliated with the organization. The CMS secretariat followed on Thursday, April 26, 2018, with an email directed to all 2,955 physicists affiliated with that experiment. Of the 5,732 physicists contacted, 518 took part in our study (ATLAS 274; CMS 244). Our overall response rate was 9% (ATLAS 9.9%; CMS 8.3%), in line with prior studies (8.3% in Wilden et al. 2013) and expectations from ATLAS and CMS management. Our respondents were mostly male (ATLAS 73%; CMS 75%), aged 41 (minimum 23, maximum 79), and at different career stages, from members of management team (ATLAS 20%; CMS 14%) to PhD students (ATLAS 40%; CMS 28%).

Procedure. The study put the participant in front of a vignette describing another scientist whose characteristics we purposefully manipulated. In particular, our design was a 2 (*locus of knowledge transfer*: internal or external) × 2 (*direct tie*: yes or no) × 2 (*reputation*: high or low) factorial design, generating a total of eight different combinations of treatments, each corresponding to one potential vignette the participant may face. Follow-up questions further differentiated between the types of knowledge involved (*strategic importance*: high or low). The vignette was introduced by a disclaimer explaining that the characteristics of the fictitious colleague were selected randomly and were not meant to identify a specific colleague. We further explained that there were no right or wrong answers, that we had no way to trace responses to the actual participant, and that only aggregated results would be shared with ATLAS and CMS management—an approach suggested by our qualitative informants with the aim of eliminating the risk of our participants being identified and reduce their concerns about social desirability.[7]

Measures. We asked our participants to imagine that the fictitious colleague described in the vignette would come to them looking for unpublished information that was internal to the collaboration. We then asked them to indicate the likelihood (on a scale from one to seven) that they would provide such information (*intended knowledge transfer*). To capture whether the knowledge was transferred across or within organizational boundaries, we manipulated the affiliation of the colleague described in the vignette, by characterizing them as affiliated with ATLAS or affiliated with CMS while at the same time collecting information about the participant's own affiliation. Hence, depending on who the participant was, the same colleague could have been perceived as affiliated with the same experiment (*internal* locus of knowledge transfer) or the other experiment (*external* locus of knowledge transfer). We chose a concrete statement of facts for our manipulation to limit demand effects: by describing a colleague as affiliated with a competing experiment, we would have risked prompting the participants to avoid any type of contact. We also manipulated other variables that, according to our informants, could explain one's propensity to transfer knowledge; namely, the existence of a *direct tie* with the colleague, their *reputation*, as well as the *strategic importance* of the knowledge transferred. We further measured those variables that, according to our qualitative examination and triangulation with extant literature, could be expected to affect the locus of knowledge transfer, namely *organizational identification*, *performance climate*, *position of responsibility*, and *based in headquarters*. Finally, we collected a series of control variables, such as gender, age, nationality, career stage, and seniority with the experiment. We provide the list of all variables and their operationalization in Table 2. Descriptive statistics and correlations are reported in Table 3.

Results

Using a randomized design ensured that treatments were orthogonal to attributes of the respondents. As such, we could estimate unbiased coefficients for the treated variables. However, to better isolate the effect of our independent variables on an individual's propensity to transfer knowledge, we provided each participant with two vignettes, thus allowing us to analyze the data by means of an ordinary least squares (OLS) regression with fixed effects and robust standard errors clustered at the level of the participant. Such a specification allowed us to control for all individual-level characteristics, as the estimation is based on differences between the two vignettes, setting aside the baseline propensity of each participant to transfer knowledge.[8]

To examine transfer preferences at ATLAS and CMS, we first ran a pooled regression including all responses (see online appendix) and then split the data to look at the behavior of the two experiments separately. Table 4 reports four models for ATLAS and four for CMS. To allow an inspection of the differences in sharing behavior across the two organizations, we started with a simple OLS with robust standard errors clustered at the participant level and individual-level controls (model 1). Next, we replicated this model using only the first vignette administered to our participants (model 2). We then moved to our preferred specification: an OLS regression with fixed effects and robust standard errors clustered at the level of the participant. This does not allow us to estimate the impact of control variables (individual-invariant characteristics are included in the fixed effects) but allows us to use all of the responses provided by our participants, including those in which a participant did not provide demographic information. Results from models 1–3 consistently show that the coefficient of *locus of knowledge transfer* has opposite signs across the two experiments: ATLAS participants reported a preference for transferring knowledge to scientists affiliated with the same experiment (model 3: $\beta = 3.614$, $p < 0.001$, confidence interval (CI): 3.128, 4.100), whereas CMS participants exhibited a preference for transferring knowledge to scientists affiliated with the other (competing) experiment (model 3: $\beta = -2.612$, $p < 0.001$, CI: −3.052, −2.172). The effects are big in size, as they represent, respectively, a +101.91% and −69.27% variation with respect to the average intention to transfer ($M_{ATLAS} = 3.546$; $M_{CMS} = 3.771$). This finding lent support to the main intuition that had emerged from Phase 1 and Phase 2 of our field

Table 2. Variables and Measures

Variable	Measure	Operationalization
Intended knowledge transfer	Participant's intention to transfer unpublished information that is internal to the collaboration	Seven-point scale, from very unlikely (1) to very likely (7)
Locus of knowledge transfer	Colleague in the vignette is affiliated with the same (vs. other) experiment	Experimentally manipulated; Same = 1, Other = 0
Direct tie	Colleague in the vignette is linked (vs. not linked) to respondent through a personal relationship (e.g., work or have worked together, know each other directly)	Experimentally manipulated; Linked = 1, Not linked = 0
Reputation	Colleague in the vignette is known to be a good (vs. mediocre) physicist in the CERN/ experiment community	Experimentally manipulated; Good = 1, Mediocre = 0
Strategic importance	Colleague in the vignette asks for information about an unexpected peak in the data (vs. a standard model measurement)	Experimentally manipulated; Peak = 1, Measurement = 0
Organizational identification	Extent to which participant feels an integral part of the organization they belong to (ATLAS vs. CMS)	Six-item scale based on Jones and Volpe (2011): from strongly disagree (1) to strongly agree (7); α = 0.82
Performance climate	Extent to which participant perceives the organization to reward employees who outperform coworkers	Eight-item scale based on Nerstad et al. (2013): from strongly disagree (1) to strongly agree (7); α = 0.73
Position of responsibility	Participant currently holds a position of responsibility or coordination in the experiment	Yes = 1; 0 otherwise
Based in headquarters	Participant's activity is primarily (≥80% of working time) located at CERN in Geneva	Yes = 1; 0 otherwise

Notes. The table provides the list of relevant variables from our laboratory-in-the-field study, with details on their operationalization.

study. In model 4, we used the same specification but inserted an additional explanatory variable, *expectation for reciprocity*, capturing the extent to which participants were expecting the fictitious colleague described in the vignette to reciprocate the favor by transferring knowledge to them in the future (on a scale from one to seven). Results show that, even when including *expectation for reciprocity* in our regressions, the effect of *locus of knowledge transfer* stays in line with what we previously observed. This seems to suggest that reciprocity, while clearly having a role to play, is not the only reason why members of these two organizations have divergent preferences relating to the locus of knowledge transfer. Our results are robust to a series of robustness tests based on the use of a generalized least squares (GLS) regression with random effects and an ordered probit.

We next examined whether it would be possible to modify the locus of knowledge transfer by acting upon the individual employee. To this end, we studied the moderating effect of job design (in our case, holding a *position of responsibility*) and socialization regime (in our case, being *based in headquarters*). Results are reported in Table 5. In models 1 and 2, we interacted *locus of knowledge transfer* with *position of responsibility*. What we observe is that scientists who hold a position of responsibility prefer to transfer knowledge within their organization rather than to members of

Table 3. Descriptive Statistics and Correlations

Variable	Mean	Standard deviation	Minimum	Maximum	1	2	3	4	5	6	7	8	9
1. Intended knowledge transfer	3.665	2.407	1.000	7.000	1.000								
2. Locus of knowledge transfer	0.479	0.500	0.000	1.000	−0.012	1.000							
3. Direct tie	0.515	0.500	0.000	1.000	0.114	0.015	1.000						
4. Reputation	0.502	0.500	0.000	1.000	0.069	0.002	−0.033	1.000					
5. Strategic importance	0.500	0.500	0.000	1.000	−0.103	0.000	0.000	0.000	1.000				
6. Organizational identification	4.674	1.275	1.000	7.000	−0.051	−0.026	−0.094	−0.069	0.000	1.000			
7. Performance climate	4.371	0.984	1.000	6.625	0.037	−0.051	−0.051	−0.003	0.000	0.170	1.000		
8. Position of responsibility	0.471	0.499	0.000	1.000	0.001	−0.020	0.031	0.011	0.000	0.101	0.041	1.000	
9. Based in headquarters	0.342	0.475	0.000	1.000	0.077	−0.016	0.044	0.029	0.000	−0.141	−0.004	0.094	1.000

Notes. The table provides descriptive statistics and correlations for relevant variables from our laboratory-in-the-field study.

Table 4. Unpacking Differences in Intended Knowledge Transfer at ATLAS and CMS

	Model 1			Model 2			Model 3			Model 4		
	Coefficient	Standard error	p value	Coefficient	Standard error	p value	Coefficient	Standard error	p value	Coefficient	Standard error	p value
ATLAS												
Locus of knowledge transfer	3.150	0.250	0.000	3.095	0.281	0.000	3.614	0.247	0.000	2.336	0.281	0.000
Direct tie	0.454	0.202	0.025	0.401	0.278	0.149	0.567	0.209	0.007	0.356	0.166	0.032
Reputation	0.446	0.179	0.013	0.432	0.273	0.113	0.415	0.183	0.023	0.191	0.169	0.257
Strategic importance	−0.358	0.080	0.000	−0.413	0.108	0.000	−0.395	0.069	0.000	−0.219	0.059	0.000
Expectations of reciprocity										0.565	0.059	0.000
Individual-level controls		Included			Included							
Individual fixed effects								Included			Included	
_cons	2.045	0.491	0.000	2.303	0.573	0.000	1.457	0.182	0.000	−0.023	0.197	0.909
N		570			286			896			896	
F	34.968		0.000	23.498		0.000	71.632		0.000	133.565		0.000
R^2 (ω)/adjusted R^2		0.465			0.461			0.534			0.684	
CMS												
Locus of knowledge transfer	−2.944	0.206	0.000	−2.988	0.235	0.000	−2.612	0.224	0.000	−1.360	0.197	0.000
Direct tie	0.023	0.177	0.897	−0.161	0.241	0.505	0.290	0.175	0.098	0.056	0.142	0.693
Reputation	0.269	0.178	0.132	0.240	0.241	0.319	0.070	0.222	0.751	−0.055	0.184	0.765
Strategic importance	−0.625	0.102	0.000	−0.650	0.134	0.000	−0.639	0.083	0.000	−0.321	0.066	0.000
Expectations of reciprocity										0.706	0.046	0.000
Individual controls		Included			Included							
Individual fixed effects								Included			Included	
_cons	7.038	0.460	0.000	7.808	0.558	0.000	5.091	0.189	0.000	1.651	0.262	0.000
N		640			320			870			862	
F	60.082		0.000	53.990		0.000	59.590		0.000	158.088		0.000
R^2 (ω)/adjusted R^2		0.453			0.490			0.426			0.656	

Notes. The table displays results of regression models whose dependent variable is *intended knowledge transfer*. We include four models for ATLAS and four models for CMS. Model 1 is a simple OLS with robust standard errors clustered at the level of the participant and individual-level controls. Model 2 replicates model 1 but only includes responses to the first vignette we administered to our participants. Model 3 includes fixed effects. Model 4 replicates model 3 with the additional control for *expectations of reciprocity*. We report adjusted R^2 for models 1 and 2 and within R^2 (ω) for models 3 and 4. Number of clusters for ATLAS: 143 in models 1 and 2; 274 in models 3 and 4. Number of clusters for CMS: 160 in models 1 and 2; 243 in model 3, and 241 in model 4. Clusters correspond to participants, and not all participants provided demographic information, which explains the lower number of clusters on the first two models. We have two to four observations per participant, depending on whether they provided answers to one or two vignettes, and considering they were asked about two types of information (high/low *strategic importance*).

the competing one. This is particularly interesting in the case of CMS scientists, given that their general preference went in the opposite direction. It should be noted, however, that the effect is not particularly strong ($\beta = 0.703$, $p = 0.133$, CI: −0.220, 1.625) and has a limited impact on the general preference for external knowledge transfer—that is, the decrease in the average intention to transfer knowledge within organizational boundaries ($M_{CMS} = 3.771$) goes from −69.27% (main effect as per model 1 in Table 4) to −63.46% (main effect and interaction effect in model 2). However, in the light of our qualitative observations and in line with recent literature suggesting that we move to a world beyond $p < 0.05$ (Wasserstein et al. 2019), we believe this finding may be worth exploring in future studies. Next, in models 3 and 4, we interacted *locus of knowledge transfer* with *based in headquarters*. What we observe is that scientists who are based in the headquarters are *more* likely to transfer knowledge to colleagues affiliated with their same experiment. Also in this case, we observe an attenuation of the general preference of CMS scientists to transfer knowledge to members of the competing organization rather than to their own colleagues. The effect is again not very strong ($\beta = 0.770$, $p = 0.081$, CI: −0.100, 1.639), but larger than what we found for *position of responsibility*—that is, the decrease in the average intention to transfer knowledge within organizational boundaries ($M_{CMS} = 3.771$) goes from −69.27% (main effect as per model 1 in Table 4) to −56.54% (main effect and interaction effect in model 4). Based on these results, we believe we found partial support for our earlier intuition that CMS scientists in positions of responsibility or based in the headquarters exhibit the opposite tendencies compared with other colleagues, in that they tend to keep knowledge inside their organization.

Discussion

Results from our laboratory-in-the-field study confirmed the intuition we had initially derived from our qualitive examination in phases 1 and 2: ATLAS participants reported a strong preference to transfer knowledge within their organization, whereas CMS participants reported a preference for transferring it to members of the competing organization, independent of whether they expect the colleague to reciprocate. This tendency among CMS scientists seemed to be partially counteracted by the job design and socialization regime: CMS participants holding a position of responsibility or based in headquarters reported opposite tendencies from their colleagues—that is, they preferred to keep knowledge inside their organization.

According to our qualitative investigation, the main reason behind these differences can be found in the different organizational climates of the two

Table 5. Unpacking Differences in Intended Knowledge Transfer at ATLAS and CMS: Role of Job Design and Socialization Regime

	Model 1 (ATLAS)			Model 2 (CMS)			Model 3 (ATLAS)			Model 4 (CMS)		
	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value
Locus of knowledge transfer (LKT)	3.401	0.426	0.000	−3.095	0.329	0.000	3.728	0.375	0.000	−2.901	0.294	0.000
Direct tie	0.585	0.211	0.005	0.297	0.185	0.109	0.566	0.208	0.007	0.264	0.177	0.135
Reputation	0.383	0.168	0.023	0.139	0.224	0.535	0.423	0.178	0.018	0.076	0.218	0.727
Strategic importance	−0.340	0.076	0.000	−0.635	0.098	0.000	−0.395	0.069	0.000	−0.639	0.083	0.000
LKT × Position of responsibility	0.910	0.506	0.072	0.703	0.467	0.133						
LKT × Based in headquarters							-0.214	0.489	0.662	0.770	0.441	0.081
Individual fixed effects		Included			Included			Included			Included	
_cons	1.433	0.181	0.000	5.233	0.196	0.000	1.461	0.182	0.000	5.081	0.184	0.000
N		606			680			896			870	
F		79.359	0.000		43.785	0.000		57.445	0.000		47.457	0.000
R^2 (ω)		0.641			0.465			0.535			0.433	

Notes. The table displays results of regression models whose dependent variable is *intended knowledge transfer*. All models are OLS regressions with fixed effects and robust standard errors clustered at the participant level. Models 1 (ATLAS) and 2 (CMS) replicate model 3 from Table 4 with the addition of the interaction between LKT and *position of responsibility*. Models 3 (ATLAS) and 4 (CMS) replicate model 3 from Table 4 with the addition of the interaction between LKT and *based in headquarters*. We report within R^2 (ω) for all models. Number of clusters for ATLAS: 152 in model 1 and 274 in model 2. Number of clusters for CMS: 170 in model 3 and 243 in model 4. Clusters correspond to participants. We have two to four observations per participant, depending on whether they provided answers to one or two vignettes, and considering they were asked about two types of information (high/low *strategic importance*).

experiments. Members of ATLAS seemed to report higher levels of identification with their organization and perceive less emphasis on outperforming coworkers. The opposite was true for CMS, which may explain the preference of CMS scientists to transfer knowledge to competitors rather than to colleagues in the same experiment. However, because our laboratory-in-the-field did not allow us to test this claim directly, at this stage we were only able to speculate that this was the reason why the two organizations exhibited opposite transfer tendencies. To be more definitive we would have needed to treat organizational identification and performance climate and then observe changes in the propensity to transfer knowledge across firm boundaries. We did not feel this was feasible in the field. More specifically, given that our qualitative examination showed these organizational characteristics to be deeply ingrained, we felt any manipulation would not be strong enough. Moreover, information from our informants suggested that attempting such a treatment would have come at the expense of the realism of our study. As a result, we chose not to manipulate these organizational characteristics at this stage and opted simply to provide evidence that a difference across ATLAS and CMS exists. Results from a mean comparison confirm that participants from ATLAS report higher organizational identification compared with participants from CMS ($\beta_{\text{ATLAS}} = 4.812$ versus $\beta_{\text{CMS}} = 4.531$, $t = 3.178$, $p = 0.002$, $d = 0.278$). Meanwhile, participants from CMS report a stronger performance climate compared with their ATLAS counterparts ($\beta_{\text{ATLAS}} = 4.272$ versus $\beta_{\text{CMS}} = 4.466$, $t = -2.849$, $p = 0.005$, $d = 0.249$). This is in line with our intuition that the two experiments differed along these dimensions.

Phase 4 and Phase 5: Refining Theory (2018–2020)

Once we had completed the first full cycle of theory building (Phase 1, Phase 2) and theory testing (Phase 3), we circled back to theory building to make sense of the empirical evidence generated by our laboratory-in-the-field study. This fourth phase of data collection took place in the second half of 2018, during which we visited CERN and conducted a number of interviews to collect feedback and refine our interpretation of the results. Once we had a working paper ready to circulate, in the beginning of 2020, we launched the fifth phase of the study, with the aim of triangulating our findings with members of both organizations.

Phase 4

While conducting the laboratory-in-the-field, we gave participants multiple ways to get in touch with us. They could leave a written comment after participating in the study—which 33 participants from ATLAS and 24 from CMS did, for a total of seven single-spaced pages. Alternatively, they could contact us directly via email; and indeed, we were contacted by eight participants from ATLAS and three from CMS. Although many comments revolved around the design of the study, the emails were mostly focused on asking for additional details or sharing suggestions on the data collection. We replied to all emails and discussed their contents with the spokespersons of the two experiments. In late May 2018, we visited CERN for two days. During this time, we met with one spokesperson at ATLAS and one at CMS to discuss preliminary results and share potential interpretations. We also arranged face-to-face interviews with nine ATLAS participants we had never met before, as well as one ATLAS and two CMS informants from Phase 1 and Phase 2 who had expressed an interest in meeting with us while we were on site.[9] Interviews lasted around 30 minutes and were not recorded at the request of our informants. However, we took notes and transcribed the key points made by each informant immediately following the meetings, for a total of five single-spaced pages of notes. We completed one last interview via video conference in June 2018 with a participant who was not at CERN during our visit but wanted to discuss their point of view with us (Informant 29). This interview lasted 39 minutes and generated 17 single-spaced pages of transcripts.

Main Insights. We leveraged the additional opportunity to interact with our participants to collect information on two findings that needed further support, namely: (a) the mediating role of organizational identification and performance climate and (b) the moderating role of job design and socialization regime.

Our research design allows us to show that ATLAS and CMS are substantially different in terms of organizational identification and performance climate. What we cannot show is that it is *because* of these differences that they exhibit opposite tendencies in their preferred locus of knowledge transfer. We hence spent some time gathering additional evidence on this point while interacting with informants. One informant reinforced the point that ATLAS scientists usually take more time before announcing any result to have a more refined understanding of what is going on. They emphasized that this usually results in CMS being faster (Informant 23). Another informant echoed this intuition when they asserted that ATLAS physicists prefer better refined analyses and more precise results before discussing their findings outside the boundaries of the organization (Informant 29). They argued that this behavior originates from ATLAS being more concerned with group objectives and less worried about competition. On the contrary, according to them, CMS scientists particularly care about beating ATLAS on time: "See, we don't really do this kind of head-to-head competition at ATLAS. We kind of try to make it more collaborative. And I think this also plays into why CMS is sometimes quicker" (Informant 29).

Comments collected at the end of the laboratory-in-the-field study were also quite telling about differences in motivational climate between the two organizations. Comments left by CMS participants hinted at a high level of competition and were focused on politics and fairness, as exemplified in the following comment: "Too often in the collaboration the decision-making process is absolutely not transparent. Only very few people participate to the decision process" (Comment 45). Similarly, another participant remarked: "The serious issue in the experiments is 'politics.' People are not rewarded according to their skills or contributions" (Comment 50). In turn, comments from ATLAS participants tended to revolve around the importance of adhering to rules and not transferring information outside organizational boundaries. In addition, ATLAS participants highlighted that competition is not very relevant, as exemplified below:

> There must be a constraint on sharing information, no matter if about a new particle or a relevant measurement. Mutual independence is what assures the relevance of observations and correctness of results.—Comment 8

Similarly, another participant noted:

> In the survey, there are many questions about competition, but there is none about self-assessment and working hard just to be able to look back and feel proud or at least satisfied that I did my best. This is what guides most of my colleagues […], even those in the most competitive positions (post-docs). If it was only for competition, most of these people could go to industry and make much more money.—Comment 19

The idea of prioritizing organizational over personal goals because of the strong level of organizational identification also emerged from what an ATLAS informant explained in one the interviews:

> It's not like: it's my result, it's your result. When that result is leaving one team and being presented outside, it's usually presented as: this is our work with everybody kind of contributing to it, even if there was a particular team behind it.—Informant 29

A second aspect we looked at more closely was related to the role of job design (in our case: holding a position of responsibility) and socialization regime (in our case: being based in the headquarters) as individual levers that organizations may act upon to mitigate the threat of external knowledge transfer. We had found only partial support for this intuition with the results from our laboratory-in-the-field study, given the limited significance of the results according to traditional indicators. However, our interviewees provided additional evidence that there may be merit in this intuition. In particular, one informant from ATLAS (Informant 29) told us: "At the management level it's like: It's not my personal goals that I'm trying to achieve, it's like I'm trying to make this community achieve a whole set of goals." This point was also raised by other informants who explained that scientists in a position of responsibility internalize rules and try to enforce them within their team through emails and personal interactions (Informant 22), thus doing their best to prevent external knowledge transfer (Informant 26). It is in this spirit that another informant concluded that the level of competition in the experiment "depends on them" (Informant 28).

In a parallel fashion, other informants claimed that younger scientists might have an incentive to break the rules by exchanging information with competitors, which might help them gain credibility and a better position in the future. With respect to this, one interviewee affiliated with ATLAS (Informant 21) added that scientists in positions of responsibility can help younger scientists understand what is appropriate when it comes to managing the knowledge generated within the organization. They recalled an episode that happened before a conference. They wanted to present something they were working on that had not gone through the approval process yet but was not very sensitive. They discussed it with their superior, who agreed to include the result in the presentation but later remove the slides from the proceedings.

Phase 5

Once we had a working paper ready to circulate, we approached the spokespersons of ATLAS and CMS to set up a joint presentation of our results to both experiments. On March 24, 2020, we presented findings from the paper in a meeting open to members of both organizations and attended by about 50 participants. We used the first half of the meeting to provide an overview of the study and its main results, while the second half was devoted to answering questions from the audience. Following the presentation, we were contacted by several members of both experiments, and we then used a snowballing technique to compile a list of additional informants to interview. We conducted 16 additional interviews between April and June. Both the meeting and the follow-up interviews were conducted online given the travel restrictions associated to the COVID-19 pandemic. Interviews were recorded and transcribed, for a total of 770 minutes of recording and 280 single-spaced pages of transcripts.

We also took detailed notes during interviews, for a total of 10 pages, which we analyzed together with the transcripts. All interviews started with us presenting the main results of the study and asking our informants to comment on them. We then followed up with a series of questions aimed at gathering additional evidence on the differences between the two organizations and better investigating the causal link between our variables of interest.

Main Insights. Following our presentation to ATLAS and CMS, we received a series of emails from scientists who wanted to follow up with us. We soon realized that this would give us the opportunity to (a) do a sanity check on the results from the field study and gather additional feedback on the mediating role of organizational identification and performance climate and (b) dig deeper into the origins of the profound differences we had identified in two organizations. With respect to the first point, this last round of interviews provided additional evidence in support of our interpretation. All our informants concurred that the two experiments were characterized by very different organizational climates and had been so since their creation. They all described CMS as dominated by a more competitive culture, and ATLAS as more cohesive, democratic, and open to leveraging collective feedback. These interviews also reinforced our intuition about the fundamental role of organizational climate in generating the differences we observed with respect to patterns of knowledge transfer. In the words of a CMS scientist:

> It is easier to speak to people from ATLAS relative to sharing internally in CMS, where you are always focused on competition […]. Talking to people from ATLAS feels like taking a moment to relax. […] You can get a completely different perspective. When you speak with CMS people, you feel inside the same box. When you talk with ATLAS people, you can refresh the ideas you have in mind.—Informant 39

When asked about whether these differences in organizational climate translate into performance differences, our informants suggested this is not the case from a quantitative standpoint:

> I don't believe that it [competition] has an effect on performance. If you look at the number of publications, there is no big difference. Competition rather affects the quality of life of researchers in the experiment, because the environment is more stressful.—Informant 34

They emphasized that the two experiments are similar in many respects, including their scientific goals:

> [When ATLAS and CMS were born] it was like: we must build a detector that works for both. ATLAS and CMS will make their individual choices, but the core technology and the core elements will be common. […] The science and the analyses are the same.—Informant 31

The fact that the two experiments were created to be as similar as possible and are indeed perfectly comparable along relevant dimensions such as mission, type of physics studied, number of employees, and location of headquarters makes the differences in organizational climate all the more striking. We had already asked our informants from Phase 2 to comment on the origins of these differences but leveraged this additional round of interviews to ask the "why" question again. In line with an argument we had heard before, some informants suggested that the founding members had different views on how members of the two experiments should perform their tasks and on how knowledge should be transferred:

> The founding members of ATLAS came from experiments like OPAL and L3, with a very collaborative history. OPAL is the best example of an experiment run like a big family, very inclusive. In OPAL there was [name] as spokesperson. This person was crucial in building the collaborative environment and the pleasure of collaboration. They were legendary. […] So, the social dimension [we have in ATLAS] derives from this culture. Our friends in CMS are more US-dominated, which influences the culture.—Informant 35

This last comment connects to a recurring theme in many interviews, in which informants mentioned the different mix of national cultures that are represented in the two experiments.

> Some academic traditions encourage information sharing and some tend to be more secretive. So, the extent to which different countries are represented in the two experiments might have some effect.—Informant 40

Despite frequent mentions, our informants concurred that the national culture element per se was not enough to explain differences between the two experiments. When asked about other reasons behind these differences, many informants mentioned a deliberate choice on the part of their organizations:

> Cultural aspects may lead to a different level of competitiveness […]. But what is interesting is the way in which the two organizations have evolved, let's say a more systemic aspect. In CMS [competitiveness] has been reinforced. […] When I discuss with colleagues from CMS, the feeling is that there is more burnout, a strong pressure to obtain results, stronger than what we have in ATLAS.—Informant 35

In line with this observation, our CMS informants gave numerous examples of how simple day-to-day operations reinforce a culture that is unanimously seen as highly competitive. One informant remarked:

> At CMS you have the following approach: You have two competing analyses A and B, you know they exist, but they don't talk to each other and they don't know much of each other. When they arrive close to publication, the collaboration asks: 'Open the boxes and show us what's inside.' […] At ATLAS we believe that this creates confusion, and it's easier to monitor step by step what was going on in the different analyses, and maybe try to understand if there is a way to converge and avoid too much competition.—Informant 31

Another mentioned the case of conference assignments, which reflects the same culture:

> At CMS, when the list of conferences is published, everyone can volunteer as a speaker, or ask someone more senior to put their name forward. So, you end up having many candidates, among which one is chosen […] based on a point system that takes into consideration when and where you have been presenting in the past. […] At ATLAS, the management makes the choice, with the aim to balance things within the group.—Informant 34

The tolerance for individual initiative is another characteristic of CMS that was mentioned as leading to higher competition: "At CMS there is a constant struggle to stand out with individual initiative within the collaboration, relative to the overall work of the collaboration" (Informant 45). Finally, we also had the chance to interview a scientist who had moved from ATLAS to CMS, who explained:

> I can see the differences in the organization of daily activities of the projects I am working on. […] The organization of CMS is more competitive, but also somehow more meritocratic. There are many competing projects that are run in parallel, […], and at the end the best one is chosen. In ATLAS, instead, you collectively merge all the inputs together. The final choice is hence owned by ATLAS, so to say.—Informant 38

Discussion

Overall, insights from our final phase of theory building paint the picture of two organizations that, despite being very similar on paper, are profoundly different in their organizational climate. Our informants suggested many possible explanations of why these differences had appeared initially and were reinforced over time. However, they all concurred that these differences deeply affect the direction of knowledge transfer in the two experiments, consistent with what we heard during our qualitative examination and found some descriptive evidence of in our laboratory-in-the-field. We next designed an experimental study in which we could manipulate organizational identification and performance climate. This allowed us to both provide a causal test of the mechanisms identified in the field and to examine actual behavior, rather than the "intention to behave" that was observable with the vignette.

Phase 6: Testing the Resulting Framework (2020)

In the final stage of data collection, we ran two experiments in which we placed participants in a simulated organizational setting, manipulated *organizational identification* or *performance climate*, and observed the effect of these variables on the choice to transfer knowledge within/across organizational boundaries. The experiments were run online due to health risks and the legally enforced restrictions in place during the COVID-19 pandemic. Although online settings may lead to the loss of experimental control (Bitektine et al. 2018), they allow researchers to tap a broader population, thus increasing external validity (Crump et al. 2013). We ran our studies on Prolific (Peer et al. 2017, Palan and Schitter 2018) and preregistered the study with the Open Science Framework (OSF), where we shared instruments, data, and code.[10]

Design

We recruited a total of 389 adults on Prolific to participate in an online study in exchange for a fixed participation fee of £3.00, independent of the participant's performance.[11] To be eligible, participants had to be located in an English-speaking country and have a good track record on the platform.[12] After accepting the informed consent, participants were randomly assigned to one of two studies. The study on organizational identification was a 2 (*organizational identification*: high/low) × 2 (*locus of knowledge transfer*: internal/external) between-subject factorial design. The study on performance climate was a 2 (*performance climate*: high/low) × 2 (*locus of knowledge transfer*: internal/external) between-subject factorial design.

Both experiments revolved around the task of filling in five missing numbers in a pyramid made of 15 numbers total, as per Figure 3. We designed the study around three successive rounds, during which participants had to solve respectively: two pyramids (practice round), four pyramids (round 1), and four pyramids (round 2). All 10 pyramids were similar in terms of difficulty and solving strategies required. We inserted mandatory 10-second breaks after each pyramid to mitigate possible fatigue effects.

Given our interest in manipulating organizational climate, we needed to assign participants to organizations.

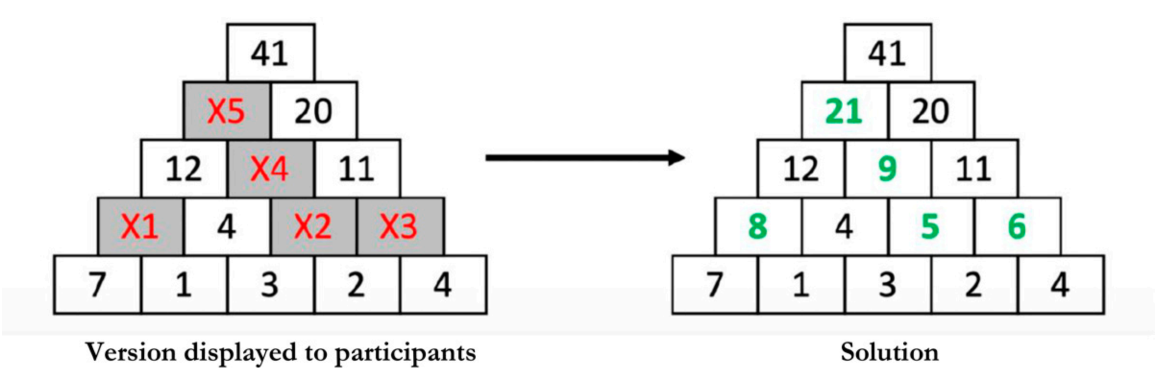
Because of the constraints of the online setting, we decided to simulate such an environment. Participants were told they would be solving number pyramids in groups of four. In reality, they were playing individually, and the information we provided them about the group setting and the other group members differed according to which experimental cell they were assigned to. We warned participants about the presence of deception in the consent form and fully debriefed them after the experiment. Deception had no effect on fairness, as all participants were compensated based on a flat fee.

Procedure. Both experiments began with a welcome screen, followed by the consent form. In the last screen of the introduction, participants were asked to enter a nickname that would be visible to other members of their team. The objective was to mimic a real-life situation so that the impression of working within a group setting was reinforced and the participant was more engaged. The experiments continued with a practice round to acclimate the participant to the experimental task, followed by two rounds during which participants were asked to solve number pyramids. Between the two rounds, we measured a participant's willingness to transfer knowledge to another participant who was either internal or external to their group. In the setting of this experiment, knowledge corresponded to solutions to the four pyramids of round 1. After making their choice about knowledge transfer, participants moved to a second round of number pyramids, which we included to increase the overall realism of the study. The second round was followed by manipulation checks, demographic questions, and a full debrief.

In addition to these common phases, the two experiments required us to manipulate either *organizational identification* or *performance climate*. To manipulate organizational identification, we replicated the protocol implemented by Schilke (2018), with some minor adjustments because of the nature of the task and the specific context of our experiment. To check the effectiveness of our manipulations, we used the four-item scale (α = 0.89) used by Schilke (2018), concluding that they were successful (M_{high} = 4.23 versus M_{low} = 3.38; $F(1,205) = 23.51$, $p < 0.001$). Results are robust to the use of the scale used in the laboratory-in-the-field (Jones and Volpe 2011). We manipulated performance climate by combining four manipulations employed in previous experimental studies investigating the effect of competition in group settings, namely Černe et al. (2014), Darnon et al. (2010), Schilke (2018), and Zhu et al. (2019). To check our manipulations, we used the same eight-item scale (α = 0.92) that we had used in the laboratory-in-the-field study (Nerstad et al. 2013). The manipulation was successful (M_{high} = 5.96 versus M_{low} = 3.46; $F(1,190) = 269.29$, $p < 0.001$). We provide additional details on the protocols in the online appendix. The exact wording of all manipulations and measures can be found in the material shared on OSF.

Measures. We manipulated organizational identification and performance climate as described previously, identifying each treatment with a dummy variable equal to one in the case of high and zero otherwise. In the case of locus of knowledge transfer, we identified internal transfer with one and external transfer with zero. Our dependent variable, *knowledge transfer*, was a count variable ranging from zero to eight and corresponding to the quantity of numbers from previously solved pyramids that were transferred to others. We controlled for gender, age group, education level, employment status, and socioeconomic status. Giving credit to the exceptional time during which the study

Figure 3. (Color online) Experimental Task



Notes. The figure shows one of such matrices as displayed to participants (image on the left) and as it should appear once it has been correctly solved (image on the right). Our laboratory experiments revolved around a mathematical puzzle: the task of solving number pyramids. The objective was to complete the puzzle by filling in five missing numbers in a pyramid made of 15 numbers total. To fill in the correct numbers, participants could add two adjacent numbers and write their sum in the block above them. Alternatively, they could use the inverse operation of subtracting a number in one of the blocks below from the number in the block above, and thereby identify the adjacent.

Table 6. Descriptive Statistics and Correlations

Variable	Mean	Standard deviation	Minimum	Maximum	1	2	3	4	5	6	7	8	9	10	11
1. *Knowledge transfer*	4.932	3.332	0.000	8.000	1.000										
2. *Organizational identification*	0.468	0.500	0.000	1.000	−0.087	1.000									
3. *Locus of knowledge transfer*	0.498	0.501	0.000	1.000	0.484	0.024	1.000								
4. *Gender*	0.444	0.498	0.000	1.000	−0.056	0.027	−0.064	1.000							
5. *Age group*	2.400	2.069	0.000	6.000	0.023	−0.182	−0.018	0.060	1.000						
6. *Education*	2.946	2.499	0.000	7.000	−0.002	0.095	0.049	0.019	0.036	1.000					
7. *Background*	6.595	3.531	0.000	10.00	−0.002	0.052	0.020	0.089	−0.197	0.045	1.000				
8. *Country of residence*	4.824	0.933	1.000	6.000	0.015	−0.044	−0.064	0.042	0.039	0.000	0.068	1.000			
9. *Employment status*	1.859	1.356	0.000	5.000	0.003	0.040	0.025	0.101	0.017	−0.002	−0.042	−0.008	1.000		
10. *Socioeconomic status*	2.732	1.155	0.000	4.000	−0.100	−0.036	−0.014	−0.150	0.035	−0.041	−0.054	0.061	−0.106	1.000	
11. *Neuroticism*	4.174	0.517	2.333	5.333	−0.084	0.014	−0.117	0.170	−0.163	−0.052	−0.090	−0.019	0.019	−0.054	1.000

Notes. The table provides descriptive statistics and correlations for relevant variables from our laboratory experiment on organizational identification.

was conducted, we also included a "pandemic control" (Laureiro-Martínez et al. 2021). To this end, we measured neuroticism, a personality trait that has been argued to play a crucial role in the extent to which an individual's behavior is affected by a pandemic (Taylor 2019). Results from a series of t tests show that all characteristics for which we controlled were evenly distributed across conditions.[13]

Results

We start by presenting evidence related to the experiment on organizational identification. Table 6 reports descriptive statistics and correlations, and Table 7 displays the results of our analyses. We ran a simple OLS (models 1 and 3) and a Poisson (models 2 and 4), in light of the fact that our dependent variable is a count variable. Results are also robust to negative binomial or ordered probit specifications. All models include robust standard errors. To look at whether treating organizational identification affects the choice of participants to transfer their knowledge within/across organizational boundaries, we interact *organizational identification* with *locus of knowledge transfer*. Across all models, the interaction term has a strong positive effect, suggesting that, when participants were treated with high organizational identification, they tended to transfer knowledge inside their own group, rather than outside of it (model 1: $\beta = 3.032$, $p < 0.001$, CI: 1.422, 4.641). The size of the effect is noticeable, as 3.032 additional numbers represent a 61% increase compared with the 4.932 numbers transferred on average in this experiment. We still observe a positive effect of comparable size when we control for whether participants were expecting the knowledge recipient to reciprocate the favor. We capture this expectation with a question we administered at the end of the experiment, where we asked "When you decided to help another participant (by sharing up to eight numbers of the pyramids solved in round 1), did you expect to receive any help in return?" As shown in models 3 and 4, the coefficient for the interaction term between *organizational identification* and *locus of knowledge transfer* stays positive and large. This suggests that the effect of organizational identification goes above and beyond the effect of reciprocity, in line with the findings of our field study.

We next move to the experiment on performance climate. Table 8 reports descriptive statistics and correlations, with Table 9 displaying the results of our analyses. Again, we used OLS (models 1 and 3) and Poisson (models 2 and 4), with results being robust to the use of negative binomial and ordered probit specifications. All models include robust standard errors. As shown in the table, the interaction term between *performance climate* and *locus of knowledge transfer* has a strong negative effect across all models. This suggests that participants treated with a high-performance climate tended to transfer knowledge outside rather than inside their group (model 1: $\beta = -1.771$, $p = 0.045$, CI: −3.502, −0.039). The size of the effect is noticeable: 1.770 fewer numbers represent a 51% decrease compared with the 3.444 numbers transferred on average in this experiment. The effect is similar in size and significance when controlling for expectations of reciprocity (models 3 and 4), in line with what we had previously observed in the field.

Discussion

Results from our experiments lend strong support to the conjecture derived from our field study, according to which an important mechanism behind difference in the preferred locus of knowledge transfer is related to differences in two features of organizational climate, namely organizational identification and performance climate. Results from our analyses show that when treated with high organizational identification, participants exhibit a strong preference for keeping knowledge within, rather than transferring it across, the boundaries of their organization (i.e., their group). On the contrary, when treated with high performance climate, participants show a strong preference for transferring knowledge to members of competing organizations rather than to their own colleagues. These findings offer support to the causal nature of the mechanisms we identified in the field study. In other words, they show that we can explain preferences in the locus of knowledge transfer as a response to differences in organizational identification and performance climate. They also come with the additional benefits of allowing us (a) to examine actual instead of intended behavior (to which we were limited in the vignette study) and (b) to generalize our intuition beyond the specific context of physicists working at CERN.

Conclusions

How can organizations motivate employees to transfer knowledge to their colleagues while at the same time exerting control over potential spillovers of proprietary knowledge to competitors? In this paper, we examined the role of organizational climate as a tool for governing knowledge transfer. Our empirical strategy consisted of a mixed-methods approach leveraging field and experimental data over two cycles of theory building and theory testing. We conducted an extensive field study of CERN and then ran two laboratory experiments aimed at providing a causal test of the emerging framework. Our findings suggest employees are more likely to transfer knowledge to their colleagues when they identify as an integral part of their organization, but would transfer knowledge to outside competitors, rather than to their

Table 7. Role of Organizational Identification in Knowledge Transfer

	Model 1			Model 2			Model 3			Model 4		
	Coefficient	Standard error	p value	Coefficient	Standard error	p value	Coefficient	Standard error	p value	Coefficient	Standard error	p value
Organizational identification (OI)	−2.153	−0.634	0.001	−0.677	−0.218	0.002	−2.214	−0.629	0.001	−0.686	−0.216	0.002
Locus of knowledge transfer	1.733	−0.615	0.005	0.334	−0.122	0.006	1.533	−0.636	0.017	0.297	−0.126	0.019
OI × Locus of knowledge transfer	3.032	−0.816	0.000	0.816	−0.231	0.000	3.225	−0.819	0.000	0.849	−0.230	0.000
Expectation of reciprocity							1.134	−0.461	0.015	0.209	−0.085	0.014
Female	−0.139	−0.442	0.754	−0.019	−0.088	0.825	−0.223	−0.436	0.610	−0.039	−0.086	0.652
Age group	−0.043	−0.110	0.697	−0.008	−0.023	0.720	−0.022	−0.109	0.838	−0.002	−0.023	0.919
Education	−0.001	−0.079	0.990	−0.001	−0.016	0.943	0.001	−0.078	0.985	−0.001	−0.016	0.964
Background	−0.009	−0.058	0.880	−0.001	−0.012	0.926	−0.003	−0.058	0.958	0.001	−0.012	0.926
Country of residence	0.164	−0.204	0.422	0.033	−0.038	0.383	0.150	−0.202	0.458	0.026	−0.038	0.483
Employment status	−0.121	−0.143	0.399	−0.023	−0.028	0.413	−0.144	−0.144	0.318	−0.025	−0.028	0.378
Socioeconomic status	−0.316	−0.184	0.086	−0.062	−0.035	0.078	−0.322	−0.181	0.077	−0.063	−0.035	0.069
Neuroticism	−0.232	−0.376	0.538	−0.056	−0.078	0.472	−0.159	−0.377	0.672	−0.034	−0.079	0.661
Cons	5.837	−2.040	0.005	1.790	−0.394	0.000	5.454	−2.034	0.008	1.687	−0.398	0.000
N		200			200			200			200	
F/Wald chi^2	11.650		0.000	71.580		0.000	12.930		0.000	81.230		0.000
Adjusted R^2/pseudo-R^2		0.295			0.120			0.313			0.126	

Notes. The table displays results of regression models whose dependent variable is *knowledge transfer*. Model 1 is a OLS regression with robust standard errors clustered at the participant level. Model 3 replicates model 1 with the additional control for *expectations of reciprocity*. Models 2 and 4 are the equivalent to models 1 and 3, only using a Poisson specification. We report F and adjusted R^2 for models 1 and 3, and Wald chi^2 and pseudo R^2 for models 2 and 4.

Table 8. Descriptive Statistics and Correlations

Variable	Mean	Standard deviation	Minimum	Maximum	1	2	3	4	5	6	7	8	9	10	11
1. *Knowledge transfer*	3.444	3.374	0.000	8.000	1.000										
2. *Performance climate*	0.519	0.501	0.000	1.000	−0.423	1.000									
3. *Locus of knowledge transfer*	0.481	0.501	0.000	1.000	−0.071	−0.025	1.000								
4. *Gender*	0.550	0.499	0.000	1.000	−0.152	−0.020	0.041	1.000							
5. *Age group*	2.259	2.094	0.000	6.000	0.013	−0.043	0.012	−0.046	1.000						
6. *Education*	2.894	2.454	0.000	7.000	0.082	−0.081	−0.023	−0.017	−0.097	1.000					
7. *Background*	6.402	3.497	0.000	10.00	0.045	0.008	−0.172	−0.012	−0.095	0.015	1.000				
8. *Country of residence*	4.905	0.820	0.000	6.000	−0.027	0.030	0.086	−0.001	−0.057	0.138	0.069	1.000			
9. *Employment status*	1.989	1.429	0.000	5.000	−0.074	0.037	0.000	0.262	−0.250	0.212	0.116	0.022	1.000		
10. *Socioeconomic status*	2.545	1.151	0.000	4.000	0.204	−0.198	0.022	−0.192	0.036	0.055	0.111	0.005	−0.100	1.000	
11. *Neuroticism*	4.129	0.524	2.111	5.444	−0.059	0.141	0.082	0.139	−0.206	−0.031	0.027	0.041	0.153	−0.029	1.000

Notes. The table provides descriptive statistics and correlations for relevant variables from our laboratory experiment on performance climate.

colleagues, when the organization encourages them to outperform coworkers. We further argue that organizations can redirect the locus of knowledge transfer internally by acting upon job design and socialization regime.

We believe our study makes several theoretical contributions. First, it contributes to literature on organizational learning (Argote and Ingram 2000, Levine and Prietula 2012) by exploring how to leverage organizational climate to manage the tension between intra- and inter-organizational knowledge transfer. Our emphasis on an informal mechanism sets us apart from prior work focusing on legal barriers and financial incentives (Agarwal et al. 2009, Gambardella et al. 2015). Exploring the effectiveness of such *soft* tools is of great importance, especially for those contexts where knowledge cannot be effectively protected using formal mechanisms (Di Stefano et al. 2014, Flammer and Kacperczyk 2019). Future research could further explore the interplay between formal and informal mechanisms in the attempt to understand, for instance, under which conditions they complement or substitute each other. Second, for literature on interest alignment (Gottschalg and Zollo 2007, Mahoney et al. 2009), we show how organizations can motivate their members to behave in line with organizational goals by acting on both organizational and individual levers. Our context is that of a complex organization, where different actors with heterogenous goals coexist and influence one another (Ethiraj and Levinthal 2009). Our case is indeed characterized by (a) individual scientists who want to advance their career, enhance their reputation, and find satisfaction in their job; (b) two experiments (ATLAS and CMS) that want to advance science, secure access to resources, and gain recognition; and finally (c) an overarching institution (CERN) that coordinates efforts and liaise with the scientific community and society as a whole. Future research could disentangle the complex interplay between the different goals of different actors. Within the context of our study, for instance, we focused on interactions between scientists affiliated with ATLAS and CMS, but we did not explore how these two experiments interact within the broader context of CERN, an organizational entity with its own management and structure. This observation about the multiplicity of goals uncovers a third contribution of our work. By examining individual and organizational goals, and by explaining individual behavior as the result of both firm- and individual-level characteristics, we contribute to literature exploring the complex interplay between micro and macro levels of analysis (Felin et al. 2015, Lee et al. 2016). This is particularly important in the domain of knowledge transfer, where previous studies have underlined the need to put knowledge exchanges “in context” (Johns 2006; Černe et al.

Table 9. Role of Performance Climate in Knowledge Transfer

	Model 1			Model 2			Model 3			Model 4		
	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value
Performance climate (PC)	−1.860	−0.685	0.007	−0.504	−0.196	0.010	−1.812	−0.669	0.007	−0.491	−0.194	0.011
Locus of knowledge transfer	0.436	−0.676	0.520	0.111	−0.140	0.427	0.278	−0.671	0.679	0.063	−0.140	0.652
PC × Locus of knowledge transfer	−1.771	-0.877	0.045	−0.768	-0.327	0.019	−1.686	−0.862	0.052	−0.751	−0.321	0.019
Expectation of reciprocity							1.426	−0.551	0.011	0.412	−0.146	0.005
Female	−0.897	−0.481	0.064	−0.246	−0.134	0.068	−1.070	−0.482	0.028	−0.309	−0.141	0.028
Age group	−0.029	−0.117	0.803	−0.003	−0.033	0.929	−0.041	−0.112	0.717	−0.006	−0.032	0.850
Education	0.050	−0.091	0.582	0.018	−0.025	0.476	0.060	−0.089	0.503	0.027	−0.026	0.296
Background	0.023	−0.063	0.710	0.006	−0.019	0.742	0.027	−0.061	0.655	0.011	−0.019	0.557
Country of residence	−0.128	−0.277	0.643	−0.039	−0.075	0.608	−0.096	−0.276	0.727	−0.033	−0.072	0.641
Employment status	−0.088	−0.160	0.582	−0.037	−0.047	0.433	−0.083	−0.152	0.586	−0.042	−0.047	0.372
Socioeconomic status	0.339	−0.205	0.100	0.102	−0.059	0.087	0.347	−0.200	0.085	0.098	−0.058	0.091
Neuroticism	0.109	−0.418	0.794	0.031	−0.118	0.790	0.118	−0.410	0.773	0.027	−0.117	0.820
Cons	4.384	−2.447	0.075	1.417	−0.607	0.020	4.010	−2.415	0.099	1.336	−0.607	0.028
N		189			189			189			189	
F/Wald chi^2		6.990	0.000		55.070	0.000		7.850	0.000		64.510	0.000
Adjusted R^2/pseudo-R^2		0.240			0.135			0.264			0.149	

Notes. The table displays results of regression models whose dependent variable is *knowledge transfer*. Model 1 is a OLS regression with robust standard errors clustered at the participant level. Model 3 replicates model 1 with the additional control for *expectations of reciprocity*. Models 2 and 4 are the equivalent to model 1 and 3, only using a Poisson specification. We report *F* and adjusted R^2 for models 1 and 3, and Wald chi^2 and pseudo R^2 for models 2 and 4.

2014, p. 186; Zhu et al. 2019), rather than considering individuals as detached from their environment.

From a methodological standpoint, our study brings two additional contributions to the emerging stream of experimental work in organizational theory and strategic management (Bitektine et al. 2018, Di Stefano and Gutierrez 2019). First, the combination of qualitative examination and experimental data over various cycles aimed at generating and verifying theory provides an example of a "full-cycle model" for research (Fine and Elsbach 2000, Mortensen and Cialdini 2010), which overcomes the artificial and the epiphenomenal nature that might be associated with experimental research (Cialdini 1980). Although such an approach might not be feasible (or necessary) in all instances, it can be helpful for scholars who want to leverage the power of experiments to unravel the complexity of organizational phenomena while also overcoming the intrinsic limitations of this method. Second, our study represents an example of how to use experiments to unearth variables that are complex to analyze in the field, as is the case for organizational climate. Despite its framed nature (Harrison and List 2004), our laboratory-in-the-field allowed us to involve real-world participants—scientists from a world-class institution, working in two of the most prestigious organizations in the domain of physics (Della Negra et al. 2012)—dealing with a knowledge transfer choice that has tremendous impact on the progress of this fundamental scientific discipline. The laboratory experiments, by contrast, revolved around simpler tasks and involved a general population of participants recruited on an online platform. However, testing our framework in such a context had the benefit of allowing us to generalize our theory beyond the specific context of our field study.

We also believe our study provides clear and actionable recommendations for managers. Our findings suggest that an unfavorable organizational climate may be tempered by acting on the individual employee. This suggests the possibility of acting at the individual level in the short run to counterbalance the effects of the unfavorable climate. In the long run, managers can also put in place more complex interventions aimed at creating an organizational climate that encourages individuals to identify with the organization and motivates them not to undermine the interests of the organization with their behavior. Another takeaway for managers, in particular for those in complex organizations, is that, despite being very similar on paper, different units can develop very different organizational traits. The most direct consequence is the need to adapt interventions to the specific "personality" of each unit. Finally, we observed considerable variance in the extent to which individuals were aware of the existence of codified norms and willing to enforce them, also because of differences in interpretation.

This suggests that mere codification of norms may not be effective unless the organizational climate is favorable to their acceptance and enforcement.

We acknowledge that our study is not without limitations, most of which we have explicitly pointed at when presenting our empirical strategy and results. An important concern that we have not discussed until now is the ability to build theory by analyzing the specific case of a science-based organization. The results of our laboratory experiments are encouraging, as they provide evidence that the conjectures derived from our examination of knowledge transfer among scientists at CERN also hold in a more general setting with different populations and different magnitudes of incentive. We believe this also reflects that the two organizations subject to our investigation are more typical than one might think. ATLAS and CMS employees work across geographical boundaries, through a mix of digital and physical interactions, in hierarchical structures that are relatively flat and leave room for personal initiatives. Despite the absence of legal consequences for transferring knowledge across organizational boundaries, engaging in such behavior can seriously affect the career progress and reputation of individual scientists, thus making the repercussions faced by scientists somewhat comparable to those faced by employees of for-profit firms. These considerations increase our confidence in the possibility for our empirical investigation to improve our understanding of how to align individual to organizational goals, and, as per our title, to stem the tide of organizational knowledge spilling across firm boundaries.

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Endnotes

[1] Knowledge produced by each single scientist is, within this context, considered knowledge that is proprietary to the experiment. The norm is that each physicist affiliated with an experiment at CERN is a contributor to the production of a broader organizational knowledge and, as such, a co-author on every major publication. Every major publication coming out of research conducted by members of ATLAS or CMS with the LHC accelerator has hence a list of ~3,000 authors. The number of authors is lower for papers called "Internal Notes." These are not intended for publication and stem from the initiative of smaller teams of physicists, who use them to diffuse information about the status of their work. Individual scientists are also allowed to write and publish a paper with a smaller team of authors, provided the work does not rely on data used in the collective publications.

[2] Given the process we followed, we did not formulate any hypotheses. However, we decided to preregister the laboratory experiments from the final phase of our study (Phase 6) as they were meant to provide a full test of the emerging theory (see link in Endnote 10).

[3] Interviews were conducted in English, French, and Italian and translated to English when needed. We were not able to record one interview because of a technical problem. Informants are identified by a number to preserve their anonymity.

[4] The Higgs Boson is an elementary particle in the standard model of particle physics. Although its existence was first theorized in the 1960s, it was not actually discovered until July 2012, the result of a research effort carried out jointly by ATLAS and CMS. See https://home.cern/topics/higgs-boson (accessed January 3, 2022).

[5] ATLAS and CMS are two *general-purpose experiments* studying a wide range of phenomena in high-energy physics. A core area of study is the Standard Model, which aims to describe the elementary subatomic particles of the universe: ATLAS and CMS study these particles and search for others to determine whether the ones we know are in fact composed of other, more fundamental ones. ATLAS and CMS also explore topics such as the constituents of dark matter or the search for extra dimensions (which could explain why the universe is expanding faster than expected and gravity is weaker than other natural forces).

[6] See https://home.cern/news/news/experiments/atlas-and-cms-celebrate-their-25th-anniversaries (accessed January 3, 2022).

[7] When negotiating access to our participants, we committed not to share individual data but only aggregated results. The management of ATLAS and CMS wanted to be reassured on this point before sending out the survey through which we administered our study. This constrains our ability to share the actual data. What we do share on the OSF is instruments, code, and an artificial data set with the aim to display the structure of our actual data set. See https://osf.io/jv73a/?view_only=8feccfb622284f16b2fd0990cb6e19e4, subfolder "Lab-in-the-field."

[8] The simplest empirical approach to answer our question would have been to assign each participant to one or the other condition (locus of knowledge transfer: internal versus external) and then look at differences across the two conditions. However, this would have put us at the risk of confounding an individual's propensity to transfer within versus across organizational boundaries (which we claim is a function of the organizational climate), with their baseline propensity to transfer (which may be the result of a variety of factors outside of the scope of this paper). For this risk to be immaterial, we would have had to assume that such baseline propensity to transfer was randomly distributed among participants of each organization. The assumption per se might be reasonable. However, given the high costs associated with collecting data in the field, we opted for a more conservative design, which enabled us to precisely

identify the effect of our treatment *net of* one's individual propensity to transfer. The administration of two vignettes, and our consequent ability to include fixed effects in the regressions, served this purpose.

[9] We speculate that the reason why only ATLAS participants spontaneously expressed an interest in meeting us is related to the fact that the ATLAS management team, different from CMS, encouraged scientists to contact us directly (see online appendix).

[10] See https://osf.io/jv73a/?view_only=8feccfb622284f16b2fd0990cb6e19e4, sub-folder "Lab Experiments."

[11] We originally recruited 480 participants. We later rejected those who failed the two attention checks we had inserted in each study, as well as those who guessed the purpose of the study. This resulted in a total of 200 participants for the experiment on organizational identification, and 189 participants for the experiment on performance climate. Results from ex post power analyses reassured us of the adequateness of our sample size.

[12] We selected participants who (a) had taken part in at least 10 studies; (b) had an approval rate of 100%; (c) held at least a high school diploma; (d) were willing to be involved in studies with deceptive elements; and (e) could participate using a laptop or PC.

[13] In the study on organizational identification, we detected a significant but small difference related to age group (lower in high group, Cohen's d = 0.33). In the study on performance climate, we detected significant but small differences related to socioeconomic status (lower in low group, Cohen's d = 0.38) and neuroticism (higher in high group, Cohen's d = 0.27).

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Online Appendix for "To Stem the Tide: Organizational Climate and the Locus of Knowledge Transfer"

Giada Di Stefano, Maria Rita Micheli

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Appendix 1.

Additional details about the analysis of interview data (Phases 1 and 2)

While the absence of interview transcripts substantially limited our ability to analyze interview data through an iterative content-analysis process (Glaser and Strauss 1967, Miles and Huberman 1994), we tried to replicate a similar process with interview notes.

We relied on all interviews from Phase 2, as well as the four interviews conducted in Phase 1 with members of ATLAS and CMS. We began by writing short descriptions of each interview to highlight key points and identify recurring patterns. We then linked each interview to a set of first-order categories (Gioia and Chittipeddi 1991, Locke 2001), capturing the elements each informant brought to our understanding of the locus of knowledge transfer. By iterating between data and theory, we were able to re-code our first-order categories into theoretically grounded second-order categories (Strauss and Corbin 1998). Fieldnotes from our observations in Geneva, together with the archival material we had collected, also guided our interpretation (Jick 1979). In this process, we repeatedly updated and revised the emerging framework based on new evidence collected through our interviews. In case of discrepancies in interpretations, we discussed to resolve them. In line with methodological prescriptions (Hirschman 1986, Lincoln and Guba 1985), we reviewed our interpretations with spokespersons from both experiments to ensure their accuracy.

We have chosen not to report this data structure in the paper because we believe the fact that it was generated mainly based on interview notes, rather than on interview transcripts, reduced its objectivity relative to methodological standards. Still, we found the exercise to be very useful, since it helped us make sense of our data and identify the emerging patterns.

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Appendix 2.

Additional details about the lab-in-the-field study (Phase 3)

Here we report additional details about design, participants, measures, and analyses for the lab-in-the-field study.[1]

Design. We administered our vignette in a survey that was initially circulated, through phone calls and email exchanges, among representatives of ATLAS and CMS. We took advantage of our CERN visit in February 2018 to pre-test the instrument with eight physicists who were not part of the management team. In addition, before the official launch of the study, we emailed the instrument to another 10 physicists who helped us to further refine it before distributing it to the entire community of ATLAS and CMS scientists. This pre-test phase allowed us to improve the wording of the questions, making sure that each was understandable and used scientific terms correctly. The study was then presented in two internal meetings of ATLAS and CMS. In Appendix 3, we report the text of the emails through which the survey was distributed by the secretary of ATLAS and the secretary of CMS. It is interesting to note that, although we gave both organizations the same sample email, they decided to slightly modify it to better fit their style. In particular, ATLAS adopted a more hands-off approach by 'inviting' members to reply and providing our emails for any questions or comments. CMS 'strongly encouraged' their members to take part in the study and centralized the collection of feedback by asking respondents to contact the management of the experiment in case they wanted to get in touch with us.

Participants. To understand whether our sample was different from the population, we asked the management of both experiments to provide us with some summary data about the recipients of the original email. Table A1 compares the population of all ATLAS and CMS scientists with our participants.

Table A1. Characteristics of Participants

	ATLAS (n=2,777)	CMS (n=2,955)	ATLAS: Participants (n=152)		CMS: Participants (n=244)		T-test		Cohen's D
	Mean	Mean	Mean	S.D.	Mean	S.D.	t	p-value	D
Gender	0.804	0.808	0.736	0.442	0.747	0.436	-0.212	0.832	0.025
PhD student	0.274	0.401	0.375	0.486	0.176	0.382	4.530	0.000	0.455
Management	0.050	0.060	0.238	0.427	0.119	0.324	3.145	0.002	0.314

Note: Only 152 of the 274 ATLAS participants responded to all demographic questions. Figures are based on available responses. The values for the t-test and Cohen's d refer to a comparison between ATLAS and CMS.

[1] Please note that the lab-in-the-field study (Phase 3) did not undergo ethical review since the procedure was not available or required by the institutions we were affiliated with at the time. In contrast, the laboratory experiments (Phase 6) underwent ethical review as in the meantime one of the authors moved to an institution where the procedure was available.

The table reveals an overrepresentation of physicists in the management team (ATLAS: $M_{Participants}$=0.238 vs. $M_{Recipients}$=0.050; CMS: $M_{Participants}$=0.119 vs. $M_{Recipients}$=0.060), which can be explained by the fact that the management of both organizations was involved with validating the experiment and organizing its distribution. To further explore any difference between ATLAS and CMS, we also conducted a series of t-tests based on the same criteria. Results show that, compared to CMS, our ATLAS sample over-represents both PhD students and physicists in the management team. The difference is not big in size (as per Cohen's d). Still, we suggest caution in making any inference, as only 152 of the 274 ATLAS participants answered our demographic questions.

Measures. Together with the main variables described in the paper, we also included other variables that, according to our qualitative informants, could explain one's intention to transfer organizational knowledge. In line with what we heard in the field, knowledge should in fact flow more easily when the counterpart is trustworthy or when the knowledge itself has less value. At the advice of our informants, we captured trustworthiness by looking at the existence of a direct tie with the colleague asking for knowledge, as well as their reputation. We manipulated the existence of a *direct tie* between the participant and the fictitious colleague by characterizing the colleague described in the vignette as 'linked to you through personal relationships, e.g. you work or have worked together, you know each other directly' (direct tie: yes) or 'NOT linked to you through personal relationships, e.g. you have never worked together, you do not know each other directly' (direct tie: no). We manipulated the *reputation* of the fictitious colleague by characterizing the colleague described in the vignette as 'known to be a good physicist in the CERN/experiment community' (reputation: high) or 'known to be a mediocre physicist in the CERN/experiment community' (reputation: low). Given that all our manipulations were concrete statements of facts, we did not insert any manipulation checks. Finally, to measure the *strategic importance* of knowledge, we asked our question about intended knowledge transfer twice, with reference to two types of knowledge. In particular, at the advice of our informants, we distinguished between 'information about an unexpected peak in the data' (strategic importance: high) and 'information about a standard model measurement' (strategic importance: low). Following each vignette, we measured the intention to transfer each of these two types of knowledge. We marked responses to the two different types with dummy variables and focused our analyses on knowledge of high strategic importance, as compared to the omitted dummy for low strategic importance. Table A2 reports the exact wording of all four treatments.

Table A2. Manipulated Variables and Corresponding Treatments

		Internal * / High †	**External * / Low †**
Colleague	Locus of knowledge transfer *	Affiliated with <*name of same experiment*>	Affiliated with <*name of competing experiment*>
	Direct tie †	Linked to you through personal relationships *e.g. you work or have worked together, you know each other directly*	NOT linked to you through personal relationships *e.g. you have never worked together, you do not know each other directly*
	Reputation †	Known to be a good physicist in the CERN/ experiment community	Known to be a mediocre physicist in the CERN/ experiment community
Knowledge	Strategic importance †	Information about an unexpected peak in the data	Information about a standard model measurement

We measured *organizational identification* using the six-item scale of Jones and Volpe (2011), where we asked participant to express their agreement with six statements about their experiment on a scale from 1 (strongly disagree) to 7 (strongly agree). Examples include: 'This experiment's successes are my successes,' or 'When someone criticizes/praises the experiment, it feels like a personal insult/compliment.' The high Cronbach's alpha (α = 0.82) supports the aggregation into a single measure. We measured *performance climate* using the eight-item scale in Nerstad et al. (2013), where we asked our participants to express their agreement with eight statements about their experiment on a scale from 1 (strongly disagree) to 7 (strongly agree). Examples include: 'Internal competition is encouraged to attain the best possible results,' or 'Work accomplishments are measured based on comparisons with the accomplishments of colleagues.' The high Cronbach's alpha (α = 0.73) supports the choice of combining the eight measures into one. At the advice of our informants, we further assessed whether participants held a position of responsibility by asking them about whether they were currently holding a position of responsibility or coordination within the experiment. The dummy *position of responsibility* equals 1 if a participant responded affirmatively to this question. Finally, location in the headquarters was assessed by asking about the percentage of time participants spent at CERN during a year. At the advice of our informants, we created a dummy *based in headquarters* equal to 1 if a participant indicated a percentage equal or above 80%.

It is important to mention that, together with information about intended knowledge transfer, we also collected information about the other five dependent variables, to have a clearer idea of the full flow of information. In particular, we asked our participants to estimate the likelihood that they would receive such a request from the colleague described in the vignette, as well as their expectation of *reciprocity* (the extent to which they expected the colleague described in the vignette to provide similar knowledge insights to them in the future). We also asked our participants to imagine the *opposite* situation, in which they would have been the ones asking the colleague in the vignette. We then asked the same three questions about their propensity to ask and to reciprocate, and the expected propensity of the colleague to transfer the knowledge they had asked for. We do not report results for these variables in this paper since they are not central to our research question.

Results. Table A3 shows the impact that *locus of knowledge transfer* has on *intended knowledge transfer* using a pooled regression including all responses from ATLAS and CMS. In particular, Model 1 does not differentiate between ATLAS and CMS, while Model 2 and Model 3 report the same results with all variables interacted with a dummy *CMS* marking all observations from CMS participants. Model 1 gives us an idea of the main drivers of the intention to transfer knowledge across both experiments. Results show that physicists are overall more likely to transfer knowledge to colleagues they know directly, and less likely to transfer knowledge of strategic importance. Neither same affiliation nor reputation seem to have any effect. The moment in which we separate the results for ATLAS from those for CMS, however, we observe the emergence of interesting differences, as predicted by our qualitative examination. We first inserted one interaction term at a time, and then ran the regression displayed in Model 2. We used the same procedure for the regression shown in Model 3. Results are consistent with those presented in the paper.

As shown in Model 2, the interaction between *locus of knowledge transfer* and *CMS* has a strong negative effect, suggesting that, compared to ATLAS participants, CMS participants reported a preference for transferring knowledge across organizational boundaries, to members of the competing experiment, rather than to colleagues from the same experiment (β=-3.113, p-value<0.001, CI: -3.440, -2.786). We also observe a strong negative effect for the interaction between *strategic importance* and *CMS*, suggesting that, compared to ATLAS participants, CMS physicists reported being less likely to transfer this type of knowledge (β=-0.122, p-value=0.023, CI: -0.227, -0.016). In Model 3, we push the comparison further by interacting *locus of knowledge transfer* with the other three independent variables, to see whether (a) the perceived trustworthiness of the counterpart (*direct tie*, *reputation*), or (b) the value of knowledge transferred (*strategic importance*) affects the intention to transfer knowledge within/across organizational boundaries. Results show that, compared to ATLAS participants, CMS participants reported a preference for transferring knowledge of strategic importance to members of the competing experiment rather than to their own colleagues (β=-0.234, p-value=0.017, CI: -0.427, -0.042).

Table A3. Examining the Drivers of Intended Knowledge Transfer

	Model 1			Model 2			Model 3		
	Coef	**SE**	**p-value**	**Coef**	**SE**	**p-value**	**Coef**	**SE**	**p-value**
Locus of knowledge transfer	0.055	0.281	0.846	0.501	0.166	0.003	0.479	0.167	0.004
Direct tie	0.653	0.199	0.001	0.429	0.136	0.002	0.438	0.135	0.001
Reputation	0.313	0.209	0.133	0.243	0.144	0.091	0.246	0.143	0.085
Strategic importance	-0.515	0.054	0.000	-0.517	0.054	0.000	-0.513	0.054	0.000
CMS * …									
… * LKT				-3.113	0.166	0.000	-2.615	0.258	0.000
… * Direct tie				-0.139	0.136	0.308	0.067	0.192	0.728
… * Reputation				-0.172	0.144	0.231	-0.005	0.187	0.978
… * Strategic importance				-0.122	0.054	0.023	-0.008	0.070	0.905
CMS * LKT *…									
… * Direct tie							-0.420	0.271	0.121
… * Reputation							-0.320	0.246	0.194
… * Strategic importance							-0.234	0.098	0.017
Individual fixed effects		Included			Included			Included	
Cons	3.285	0.215	0.000	3.247	0.131	0.000	3.249	0.130	0.000
N		1,766			1,766			1,766	
F	27.028		0.000	65.738		0.000	48.986		0.000
R^2 (ω)		0.051			0.482			0.487	

Note: The table displays results of regression models whose dependent variable is *intended knowledge transfer*. All models are OLS regressions with fixed effects and robust standard errors clustered at the participant level. We report within R^2 (ω) for all models. Number of clusters: 517. Clusters correspond to participants We have 2 to 4 observations per participant, depending on whether they provided answers to 1 or 2 vignettes, and considering they were asked about 2 types of information (high/low *strategic importance*).
Model 1 includes main effects only, Model 2 interacts the main effects with the affiliation of the participant (CMS vs. ATLAS), Model 3 adds the three-way interactions with our main variable of interest (*locus of knowledge transfer*, which we abbreviate in LKT).

Models 1 and 2 of Table A4 (where we split the observations between ATLAS and CMS participants) allows us to more easily interpret this three-way interaction. Results show that the effect is driven by the behavior of our ATLAS participants, who reported being *more* likely to transfer knowledge of high strategic importance if the colleague asking for it is affiliated with the same experiment (β=0.301, p-value=0.026, CI: 0.035, 0.567). In other words, at ATLAS *locus of knowledge transfer* reverts the result on *strategic importance*. It is worth noting that the results reported below, as well as in the paper, are indicative of an intention to transfer knowledge, given that we put participants in front of a vignette and asked them about the extent to which they were likely to transfer knowledge to the colleague described there. To complement our study of intent, we further analyzed behavioral data available for participants in the lab-in-the-field study and collected additional secondary data that could proxy for the knowledge flows of interest.

Table A4. Unpacking Differences in Intended Knowledge Transfer at ATLAS and CMS

	Model 1 ATLAS			Model 2 CMS		
	Coef	SE	p-value	Coef	SE	p-value
Locus of knowledge transfer (LKT)	2.901	0.429	0.000	-2.264	0.313	0.000
Direct tie	0.268	0.299	0.371	0.420	0.249	0.092
Reputation	0.217	0.237	0.360	0.222	0.290	0.444
Strategic importance	-0.536	0.093	0.000	-0.556	0.105	0.000
LKT * Direct tie	0.646	0.435	0.138	-0.255	0.345	0.461
LKT * Reputation	0.382	0.332	0.251	-0.291	0.370	0.431
LKT * Strategic importance	0.301	0.135	0.026	-0.166	0.143	0.246
Individual fixed effects		Included			Included	
Cons	1.796	0.247	0.000	4.908	0.222	0.000
N		896			870	
F	44.547		0.000	34.369		0.000
R^2 (ω)		0.542			0.428	

Note: The table displays results of regression models whose dependent variable is *intended knowledge transfer*. All models are OLS regressions with fixed effects and robust standard errors clustered at the participant level. We report within R^2 (ω) for all models. Model 1 includes only responses from ATLAS participants (274 clusters). Model 2 includes only responses from CMS participants (244 clusters).

With respect to the lab-in-the-field, we focused our attention on two observable behaviors, namely the amount of time each participant took to complete the study, as well as their propensity to leave a comment at the end of it. Our argument is the following: if members of ATLAS(/CMS) are more likely to transfer knowledge to a colleague from the same (/other) experiment, then facing such a counterpart should make them more likely to transfer not only the knowledge described in the vignette, but also their knowledge more broadly—a tendency that we can capture by looking at the amount of time each participant took to complete the study, as well as to their propensity to leave a comment at the end. Table A5 and Table A6 report the results of these analyses. Note that we ran the analyses for both dependent variables using two different samples: one consisting of all observations, and another including only those participants who received an identical affiliation treatment across the two vignettes (i.e., always a colleague from the same experiment, or always a colleague from the competing experiment, while the other treatments were changing). There are no substantial differences among models, but we believe that the second specification, despite the lower number of observations, should better capture what we are interested in, given that the participants did not receive conflicting stimuli. Results are directional, even if not particularly strong in terms of significance. When the colleague described in the vignette was a colleague from the same organization, members of ATLAS spent more time on the study and were more likely to leave a comment. On the contrary, when the colleague described in the vignette was a colleague from the same organization, members of CMS spent less time on the study and were more likely to leave a comment.

Analyzing these data represents a first attempt at gathering behavioral evidence of the differences between ATLAS and CMS scientists. We next tried to collect data more broadly for ATLAS and CMS, independent of our study. In the context of science, collaboration among scientists is usually reflected in the number of scientific works developed together, namely papers. We hence turned to the CERN archives, as well as to arXiv, an open-access repository where almost all papers and preprints in physics are self-archived. Given our interest in examining the transfer of organizational knowledge (remember our vignette asking to think of a colleague looking for "*unpublished information that is internal to the collaboration*"), we did not focus on published papers, but rather on preprints (which physicists can make available both in CERN archives and on arXiv) and notes (a CERN-specific format used both internally and publicly to share updates on specific analyses or on the necessary steps to reach future stages of experiments' evolution). Focusing on preprints and notes also allowed us to better capture individual research outputs of CERN scientists; in fact, published papers are usually signed by all members of the experiment, while preprints and notes are the result of personal initiatives of scientists, who can choose whom to collaborate (see footnote 2 in the paper). What we discovered in the process was quite telling. First, out of the 395 notes relying on analyses run by both ATLAS and CMS, 61.77% were submitted by CMS scientists, while only 38.23% were submitted by ATLAS scientists. This may allude to a higher tendency for CMS scientists to develop work based on knowledge originating from both organizations. We found similar results for preprints. When looking at those stored in CERN archives, out of 111 preprints relying on analyses run by both ATLAS and CMS, we found that 76.58% were submitted by CMS scientists, while only 23.42% were submitted by ATLAS scientists. We found somewhat similar evidence when looking at unpublished papers co-authored by members of both ATLAS and CMS and uploaded on arXiv. Out of 93 papers, 51 were uploaded by CMS authors, potentially suggesting a higher propensity to initiate collaboration opportunities. Despite descriptive, these additional data reinforced our intuition that members of ATLAS would be more likely to transfer knowledge to colleagues from the same organization, while the opposite would be true for members of CMS.

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Table A5. Time Taken to Complete Study (Minutes)

	ATLAS						CMS					
		Model 1			Model 2			Model 3			Model 4	
	Coef	**SE**	**p-value**	**Coef**	**SE**	**p-value**	**Coef**	**SE**	**p-value**	**Coef**	**SE**	**p-value**
LKT	7.277	5.524	0.188	14.721	12.510	0.239	-6.354	5.060	0.209	-14.732	10.513	0.161
Direct tie	-4.768	5.468	0.383	-4.059	3.832	0.290	-4.857	8.115	0.549	11.905	11.958	0.319
Reputation	-5.321	4.063	0.190	3.926	3.425	0.252	-15.949	9.007	0.077	-11.999	11.292	0.288
Controls		Included			Included			Included			Included	
_cons	17.284	14.710	0.240	1.741	9.268	0.851	2.754	25.143	0.913	-11.259	22.662	0.619
N		570			312			640			284	
F	0.870		0.534	0.740		0.640	0.970		0.458	0.450		0.865
Adjusted R^2		0.013			0.096			0.035			0.062	

Note: The table displays results of regression models whose dependent variable is the number of minutes taken by our participants to complete the study. All models are OLS regressions with robust standard errors clustered at the participant level. Within R^2 (ω) reported for all models. Model 1 (ATLAS) and Model 3 (CMS) include all observations, Model 2 (ATLAS) and Model 4 (CMS) only include participants who received the same treatment for *locus of knowledge transfer* (abbreviated in LKT) twice. Number of clusters for ATLAS: 143 in Model 1, 78 in Model 2. Number of clusters for CMS: 160 in Model 1, 71 in Model 2. Clusters correspond to participants. We have 1 to 2 observations per participant, depending on whether they provided answers to 1 or 2 vignettes.

Table A6. Likelihood of Leaving a Comment After the Study

	ATLAS						CMS					
		Model 1			Model 2			Model 3			Model 4	
	Coef	**SE**	**p-value**	**Coef**	**SE**	**p-value**	**Coef**	**SE**	**p-value**	**Coef**	**SE**	**p-value**
LKT	0.471	0.346	0.174	0.951	0.620	0.125	-0.364	0.299	0.224	-0.815	0.799	0.307
Direct tie	-0.195	0.331	0.555	-0.401	0.417	0.336	0.214	0.350	0.542	-0.160	0.506	0.752
Reputation	-0.545	0.336	0.105	-0.102	0.465	0.827	0.342	0.353	0.333	0.355	0.615	0.563
Controls		Included			Included			Included			Included	
_cons	-1.801	1.006	0.339	-2.141	1.222	0.621	-1.750	0.984	0.561	-0.595	1.429	0.542
N		570			312			640			284	
Wald chi²	12.060		0.099	9.470		0.220	4.330		0.741	6.470		0.486
Pseudo R^2		0.058			0.116			0.018			0.081	

Note: The table displays results of regression models whose dependent variable is the likelihood of leaving a comment at the end of the study. All models are logit models with robust standard errors clustered at the participant level. Pseudo R^2 reported for all models. Model 1 (ATLAS) and Model 3 (CMS) include all observation, Model 2 (ATLAS) and Model 4 (CMS) only include participants who received the same treatment for *locus of knowledge transfer* (abbreviated in LKT) twice. Number of clusters for ATLAS: 143 in Model 1, 78 in Model 2. Number of clusters for CMS: 160 in Model 1, 71 in Model 2. Clusters correspond to participants. We have 1 to 2 observations per participant, depending on whether they provided answers to 1 or 2 vignettes.

Appendix 3.

Emails through which lab-in-the-field study (Phase 3) was distributed

1. ATLAS email sent February 26, 2018

Dear Colleagues,

The management of ATLAS has agreed to conduct a study on information transfer among colleagues at CERN.

This study is conducted by two researchers:
- Researcher #1: First name, Last name – Rank, Affiliation, Website
- Researcher #2: First name, Last name – Rank, Affiliation, Website

You are invited to reply to the survey, which takes **less than 10 minutes** to complete. The deadline is **March 9th, 2018**.

Please click: <direct link to survey>
If the link above does not work, please go to: <webpage>

Results from the survey will be presented in a web-cast event. You will also receive a detailed research report with all the main insights.

If you have any question or comment, please feel free to directly contact Researcher #1 (email) and Researcher #2 (email).

Thank you for your collaboration!

Names of spokespersons

2. CMS email sent April 26, 2018

Dear Colleagues,

The management of CMS, with CERN support, has agreed to conduct a study on information transfer among physicists at CERN.

For this study, we are collaborating with two researchers:

- Researcher #1: First name, Last name – Rank, Affiliation, Website
- Researcher #2: First name, Last name – Rank, Affiliation, Website

You are strongly encouraged to reply to the survey, which takes **less than 10 minutes** to complete. The deadline is **May 8th, 2018**.

Please click: <direct link to survey>

Results from the survey will be presented in a web-cast event. We will also receive a detailed research report with all the main insights.

If you have any questions or comments, please pass them along to us and we will transmit them to the survey team leaders.

Thank you for your collaboration!

Names of spokespersons

Appendix 4.

Additional details about the lab experiments (Phase 6)

Here we report additional details about the design of our lab experiments. To manipulate organizational identification, we replicated the protocol implemented by Schilke (2018), with some minor adjustments due to the nature of the task and the specific context of our experiment. This protocol involved the use of three subsequent manipulations, which were administered before the practice round for participants in the 'high' condition and after the second round for participants in the 'low' condition. The first manipulation consisted of a test aimed at testing one's problem-solving approach, a test that respondents in the high-identification condition were led to believe would be the rationale for allocating them to a specific group for the continuation of the study (Doosje et al. 1995, Schilke 2018). In reality, all participants received the same result, but participants in the high-identification condition were told that they had been allocated to a group of people who shared the same problem-solving approach—a feature that enabled us to stimulate intergroup comparison, with a positive effect on group identification, as per Kramer and Brewer (1984). Participants in the high-identification condition were also asked to confirm that they would like to continue with such group—which enabled us to underline voluntary commitment to the group, with a positive effect on group identification, as proposed by Turner et al. (1984). Our second manipulation consisted of a reward-allocation task (Tajfel 1971) whose aim was to allocate rewards/penalties to members of one's group vs. members of another group—an activity that has been associated with creating a higher identification with one's group (Leyens et al. 1994). Finally, participants were asked to complete a group involvement test consisting of five questions aimed at measuring the extent to which group members felt involved with their group (Doosje et al. 1995, Schilke 2018). After answering these questions, participants in the high-identification condition were informed that their group reported a higher-than-average group involvement score (53 vs. 40), while participants in the low-identification condition were informed that their group reported a lower- than-average group involvement score (27 vs. 40). As before, this information did not reflect a true result; it was a deceptive feature participants were informed about at the end of the study. To check the effectiveness of our manipulations, we used the four-item scale ($\alpha = 0.89$) employed by Schilke (2018), concluding that they were successful ($M_{high}= 4.23$ vs. $M_{low}=3.38$; $F (1, 205) = 23.51$, p-value<0.001). As a robustness test, we included the same six-item scale ($\alpha = 0.87$) we employed in the lab-in-the-field (Jones and Volpe 2011). We found that identification was higher in the high condition ($M_{high}= 4.35$ vs. $M_{low}=4.03$; $F (1, 205) = 2.80$, $p = 0.09$). Following Schilke (2018), we also looked at points allocated to in-group members in the reward allocation task and found that the amount of points allocated was greater in the high condition (M_{high}= 36.11 vs. M_{low}=31.13; $F (1, 205) = 2.21$, $p = 0.14$).

We manipulated performance climate by combining four different manipulations employed in previous experimental studies investigating the effect of competition in group settings. We administered the first two manipulations before the practice round and the last two before and after the first round, respectively. The first manipulation provided participants with important information on the objective of the study and was designed following Černe et al. (2014) and Darnon et al. (2010). In particular, participants in the 'high' condition were encouraged to perform better than their group members, while those in the 'low' condition were encouraged to strive for personal improvement. The structure and rationale of the second manipulation followed Schilke (2018), building on the work by Gioia and Thomas (1996). We started by asking our participants to select a personal motto among three versions reinforcing the concepts previously introduced. After having chosen their motto, participants were informed about the choices of their group members—again reinforcing the concepts introduced in the first manipulation. Once the practice round was completed, participants waited for their fictitious group members to finish and were shown completion feedback that served as our third manipulation, designed based on the work of Zhu et al. (2019). In particular, participants in the 'high' condition were provided with individually focused feedback that compared their performance with that of a subset of their group members,[2] thereby directing their attention to personal achievement. In contrast, participants in the 'low' condition were shown generic feedback without any peer comparison. Our last manipulation consisted of an almost identical repetition of the previous one, placed just before the measurement of the dependent variable. While the design and rationale were identical, the manipulation differed with respect to the gap between the participant's performance and the performance of the other two group members. Compared to the initial feedback, the participant now perceived an improvement in their relative position within the group. This reduced fear of failure that, according to Darnon et al. (2007), may induce performance-avoidance and thus reduce the effectiveness of our previous manipulations. To check our manipulations, we used the same eight-item scale (α = 0.92) that we had employed in the lab-in-the-field study (Nerstad et al. 2013). The manipulation was successful (M_{high}= 5.96 vs. M_{low}=3.46; $F (1, 190) = 269.29$, p-value<0.001).

[2] We included only two group members in the comparison set so that participants could perceive social comparison without knowing their absolute position within the group.

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