

**The Division of Labor in Teams:
A Conceptual Framework and Application to Collaborations in Science**

Carolin Haeussler
University of Passau
carolin.haeussler@uni-passau.de

Henry Sauermann
Georgia Institute of Technology, Scheller College of Business
National Bureau of Economic Research (NBER)
henry.sauermann@scheller.gatech.edu

ABSTRACT

Even though teams are the dominant source of new knowledge, we have little understanding how they divide work among their members. Conceptualizing knowledge production as a process involving a number of functional activities, we first develop a theoretical framework to study the division of labor in teams. This framework highlights three complementary perspectives: (1) individual-level (the degree to which team members specialize in a small number of activities), (2) activity-level (the degree to which activities are concentrated among few team members vs. distributed among many) and (3) the intersection between the two. We then use this framework to analyze a newly available type of data on team-based knowledge production – disclosures of author contributions on scientific papers. Using data from over 12,000 articles, we provide unique descriptive insights into patterns of division of labor, demonstrating the value of the three complementary perspectives. We also apply the framework to uncover differences in the division of labor in teams of different size, working in novel vs. established fields, and on single vs. interdisciplinary projects. Finally, we show that division of labor is significantly related to the quality of teams' research output. We discuss opportunities for future research as well as implications for scientists and policy makers.

JEL Classification Numbers: O31, O32, J2

Keywords: Team Production, Knowledge Work, Collaboration, Division of Labor

Acknowledgement: We thank participants in several seminars and conferences for extremely helpful comments and discussions. We thank Mayank Jaiswal and Maria Roche for excellent research assistance. All errors are our own.

1 Introduction

A growing body of research examines the organization of knowledge production and the role of collaboration in teams. One stream of work conceptualizes innovation as the recombination of prior pieces of knowledge (Simonton, 2003; Gruber et al., 2013), suggesting that the collaboration of specialized researchers with knowledge in different domains may allow teams to push deeper towards the knowledge frontier and to create more novel combinations of knowledge (Jones, 2009; Singh & Fleming, 2010; Bercovitz & Feldman, 2011; Teodoridis, 2013). A complementary view emphasizes that research involves a number of different functional tasks, ranging from the generation of research hypotheses and the design of experiments to the codification of research results in a scientific paper (Hagstrom, 1964; Latour & Woolgar, 1979; Knorr-Cetina, 1999; Owen-Smith, 2001; Bikard et al., 2015). This view is also implicit in recent portrayals of the “lab as a firm”, which suggest that competition leads labs to pursue efficient knowledge production by relying on the division of labor among specialized team members (Hackett, 1990; Freeman et al., 2001; Stephan, 2012). Despite rich qualitative discussions, however, we have a limited understanding of the division of labor in teams. For one, prior work has discussed teams’ internal organization from different angles, yet we lack a standard framework that clarifies how division of labor can be conceptualized and measured. Just as importantly, the internal organization of teams often remains hidden from outsiders and there is little large-scale empirical evidence on the division of labor in collaborative knowledge production (Stephan, 2012; Shibayama et al., 2015).

This paper makes two main contributions. First, we develop a conceptual framework that highlights three complementary aspects of division of labor in teams: Focusing on individuals and looking across activities, the first perspective informs us about the degree to which members specialize in a small number of activities vs. perform a broader range of activities. Focusing on activities and looking across team members, the second perspective informs us about the degree to which an activity is distributed across many team members vs. concentrated among a few. Looking across both individuals and activities, the third perspective informs us about the relationships among activities, e.g., which activities tend to be performed jointly by the same individuals. While prior work focuses on selected aspects of division of labor, our framework integrates multiple perspectives and highlights their complementarities. As such, it provides a useful basis for understanding and mapping the division of labor in teams and may stimulate future theoretical and empirical work.

Second, we utilize our framework to analyze novel data on the division of labor in scientific teams. While information on individual team members’ activities is typically difficult to obtain, an increasing number of journals require that articles disclose which authors made which contributions. Using data from over 12,000 such articles - mostly in the biological sciences and medicine – we make a number of observations. First, while division of labor can be summarized using team-level measures,

measures at the level of individual scientists or activities provide important complementary insights. Even in a given team, some individuals are much more specialized than others, and activities differ in the degree to which they are distributed among members. Similarly, while some activities –such as data analysis and writing – are commonly performed jointly with other activities, experimental work or the supply of materials are often performed in isolation. Consistent with prior theory, we also find that division of labor increases with team size. Again, however, there is significant heterogeneity across activities. While larger teams involve a correspondingly larger number of individuals in empirical activities, the number of members engaged in conceptual activities or in writing grows much more slowly with team size. In addition to mapping these basic patterns of division of labor, we examine how division of labor differs across types of projects. We find that teams in novel fields use significantly higher division of labor than those working in established fields, and the functional division of labor is lower in interdisciplinary projects. Applying our framework, we further clarify the nature of these differences by exploring individual versus activity level aspects of division of labor. Finally, we use citations to examine how different aspects of division of labor in a team relate to the scientific impact of the resulting paper.

Our work contributes to a number of literatures. First, we contribute to the organizational literature by developing a conceptual framework of different aspects of division of labor in teams and by suggesting a number of related measures at different levels of analysis. This framework may be useful for future efforts to study the organization of teams across a broad range of contexts. Empirically, much of the prior work has focused implicitly or explicitly on the production of physical goods (Smith, 1776; Hamilton et al., 2003). We consider how some of the fundamental concepts from that literature translate into the increasingly important context of team-based knowledge production and introduce a novel data source that should prove useful for future research.

Our insights also contribute to a growing literature on the production of knowledge and the economics of science (Dasgupta & David, 1994; Wuchty et al., 2007; Singh & Fleming, 2010; Jones & Weinberg, 2011; Stephan, 2012). Complementing the common focus on collaborators as contributors of different pieces of knowledge, we focus on their role in performing different types of functional activities.¹ Using our conceptual framework and exploiting a newly available data source, we then provide descriptive insights into the process of knowledge production in teams. Our analyses exploring division of labor in different types of projects and its relationship with the quality of scientific output also point towards promising avenues for future research on the drivers of division of labor and its role in shaping innovative performance.

¹ While activities clearly draw on knowledge, the division of labor can differ significantly from the partitioning of knowledge (Postrel, 2002; Takeishi, 2002). For example, different sets of knowledge may be employed to perform a given activity. Similarly, some team members may not perform certain activities even though they would possess the required knowledge.

Our conceptual framework and empirical results may also be useful for scientists as well as for policy makers. For example, insights regarding the degree to which scientists specialize in certain activities may inform current debates concerning the content and process of science education (Freeman et al., 2001; Agarwal & Sonka, 2010; Fuhrmann et al., 2011). Similarly, thinking about factors that enable or constrain division of labor may help scientists as they consider the benefits or costs of forming larger teams (Gans & Murray, 2013) or as they explore new forms of organizing science such as the crowdsourcing of certain parts of the research process (Nielsen, 2011; Franzoni & Sauerermann, 2014).

2 Conceptual Framework

2.1 Conceptualizing division of labor in teams

Scholars have examined the division of labor at different levels of analysis (e.g., Smith, 1776; Hagstrom, 1964; Gibbs & Poston, 1975; Becker & Murphy, 1992; Arora et al., 2014; Puranam et al., 2014). We draw on these discussions to develop a conceptual framework that allows us to map and analyze the division of labor in teams. This framework highlights several complementary perspectives and also points towards ways to operationalize and analyze division of labor empirically.

We start from the premise that the production of a certain output (e.g., a piece of new knowledge) requires the completion of a number of ($j=1 \dots K$) distinct activities or tasks. These activities can be distributed among a number of ($i=1 \dots N$) team members. To conceptualize division of labor, it is useful to represent team members and activities in a matrix structure. For illustration, consider the stylized example of two teams shown in Figure 1. For each team, the columns refer to a set of different functional activities that need to be performed to produce an output. The rows refer to team members who collaborate by performing these activities. The indicator a_{ij} in each of the resulting cells indicates whether a particular member i performs activity j ($a_{ij}=1$) or not ($a_{ij}=0$).² Figure 1 shows that division of labor can be examined using three complementary perspectives: the degree to which team members specialize in one task vs. perform a range of tasks (within individuals, across activities), the degree to which activities are performed by one person versus multiple persons (within activities, across individuals), and the degree to which activities tend to be performed together by the same individuals (across individuals and activities). We will discuss each in turn.

From the perspective of individual team members, we can examine how many of the activities a member is engaged in. In particular, we can compute the measure $G_i = \frac{\sum_{j=1}^K a_{ij}}{K}$, which describes the degree to which individual i performs a broad range of activities (“*generalist*”) or is specialized by performing

² Our main discussion abstracts from the amount of time spent on an activity. The Appendix extends this framework to include different shares and levels of effort devoted to different activities, which allows us to compute Herfindahl-based measures.

only a small share of the activities (“*specialist*”). G_i ranges from 1 in the extreme case that a team member performs all of the K activities to $G_i=1/K$ if the individual performs only one activity. To illustrate using Figure 1, individual 1 in team A performs 1 out of 4 activities and is thus highly specialized ($G_i=0.25$) while individual 2 in team A performs 2 out of 4 activities and is thus less specialized ($G_i=0.50$). We can average all N team members’ scores and use this team-level measure, $G_t = \frac{\sum_{i=1}^N G_i}{N}$, to compare the average degree of specialization across teams. Using the example in Figure 1, we see that team A is more specialized than team B: The average member performs only 30% of all tasks compared to 70% in team B.

Complementing the individual-level perspective, an activity-level perspective examines by how many of the N team members a particular activity is performed. More specifically, the measure $D_j = \frac{\sum_{i=1}^N \alpha_{ij}}{N}$ captures the share of team members who perform activity j . We will term activities that are performed by many team members (in the extreme all team members such that $D_j=1$) as highly *distributed*. Activities that are performed by only a small share of team members are more *concentrated*, with an extreme score of $D_j=1/N$. To illustrate, activity 1 in team A is performed by one individual ($D_j=0.2$) and is thus highly concentrated, while activity 2 is performed by two individuals ($D_j=0.4$) and is more distributed. Averaging across all K activities results in the team-level measure $D_t = \frac{\sum_{j=1}^K D_j}{K}$. In our example, the average activity in Team A is performed by 30% of all team members, while the average activity in Team B is performed by 70% of the team members.

Note that the team level measures G_t and D_t are equivalent (i.e., $\frac{\sum_{i=1}^N G_i}{N} = \frac{\sum_{j=1}^K D_j}{K}$), such that a higher degree of specialization of team members also implies a higher concentration of activities and vice versa. However, de-aggregating these measures allows us to better understand heterogeneity within the team: the individual perspective allows us to distinguish specialist vs. generalist members, while the activity-level perspective allows us to distinguish activities that are distributed among many members vs. concentrated among a few.

Figure 1: Conceptualizing division of labor in teams

TEAM A								TEAM B									
	Activity				Count of activities	Share of activities (G _i)	Activity				Count of activities	Share of activities (G _i)					
	1	2	3	4			1	2	3	4							
Member	1	1	0	0	0	1	25%	Member	1	1	1	0	1	3	75%		
	2	0	1	0	0	1	25%		2	1	1	0	1	3	75%		
	3	0	0	0	1	1	25%		3	0	0	1	0	1	25%		
	4	0	0	0	1	1	25%		4	1	1	0	1	3	75%		
	5	0	1	1	0	2	50%		5	1	1	1	1	4	100%		
Avg. (G_i): 30%						Avg. (G_i): 70%											
Count of members	1	2	1	2													
Share of members (D_j)	20%	40%	20%	40%	Avg. (D_j): 30%				4	4	2	4	Share of members (D_j) 80% 80% 40% 80% Avg. (D_j): 70%				
Correlations (ρ_{jl})								Correlations (ρ_{jl})									
	Act. 1	Act. 2	Act. 3	Act. 4					Act. 1	Act. 2	Act. 3	Act. 4					
Act. 1		-0.41	-0.25	-0.41					Act. 1	1.00	-0.61	1.00					
Act. 2			0.61	-0.67					Act. 2		-0.61	1.00					
Act. 3				-0.41					Act. 3			-0.61	-0.61				
Avg. ρ_{jl} (I_j)	-0.36	-0.15	-0.02	-0.49					Avg. ρ_{jl} (I_j)	0.46	0.46	-0.61	0.46				
Avg. I_j (I_i)				-0.25					Avg. I_j (I_i)				0.19				

Finally, a third perspective looks across both individuals and activities. This perspective provides insights into the relationships among activities, i.e., which activities tend to be performed together by the same individuals and which activities are performed separately from each other. For example, in team B, individuals who perform activity 1 always perform activity 2 as well, resulting in a positive correlation. In contrast, individuals who perform activity 1 tend not to be involved in activity 3, resulting in a negative correlation between these two activities. Denoting the correlation between activity j and another activity l ($l=1 \dots K$, with $l \neq j$) as ρ_{jl} , the average correlation of activity j with other activities can be computed as

$$I_j = \frac{\sum_{l=1}^K \rho_{jl}}{K-1}$$

Activities that tend to be positively correlated could be called *interdependent*, while those that

tend to have negative relationships with other activities are more *independent*. Averaging all correlations

between activities at the team level results in the team level measure $I_i = \frac{\sum_{j=1}^K I_j}{K}$.³

³ One could also examine correlations between team members, i.e., which team members tend to work together on the same activities and which team members tend to work on different activities. We focus on correlations among activities since these relationships are more relevant from an organizational perspective (see section 2.2). Also, while our illustrative examples use the commonly used Pearson product-moment correlation coefficients, one could consider other measures of association.

2.2 Potential efficiency gains from division of labor

The conceptual framework allows us to characterize division of labor in teams using three perspectives. We now draw on prior work in organizational theory and economics to briefly highlight mechanisms that have been proposed to explain each of the three aspects of division of labor. In doing so, we focus primarily on arguments made by economists and organizational theorists, who emphasize potential efficiency gains from division of labor (Smith, 1776; Hagstrom, 1964; Becker & Murphy, 1992). The objective of our discussion is not to derive testable hypotheses but to connect the framework more explicitly to the prior literature. We will also return to this discussion in considering the degree to which empirical patterns of division of labor observed in the second part of the paper are consistent with mechanisms suggested in the prior literature.

A first argument is that specializing in a particular activity may allow individuals to acquire knowledge about how to perform this activity more efficiently (“learning by doing”). Moreover, learning may become increasingly easy as an individual’s stock of knowledge in a particular domain increases (Postrel, 2002). To the extent that such learning benefits can be realized, a worker should focus on one activity rather than splitting her time across multiple different activities, implying a higher degree of specialization (our measure G_i from Section 2.1) and more division of labor.

Second, if an activity requires worker-specific investments such as tools or instruments but also stocks of knowledge, having one person focus on this activity avoids the duplication of investments and allows the existing capital to be utilized more efficiently. Thus, to the extent that workers have to incur fixed costs to perform an activity, the number of individuals working on that activity should be minimized, implying a higher degree of concentration (i.e., our D_i) and more division of labor.

Potential benefits from specialization and concentration, however, may be offset by increasing costs of coordinating the activities of different team members. One driver of these costs are interdependencies between activities (Simon, 1962; Becker & Murphy, 1992; Cummings & Kiesler, 2014; Puranam et al., 2014). As highlighted by organizational theorists, interdependencies between activities can differ in terms of both the frequency and the sequencing of work flows (Thompson, 1967; Van de Ven et al., 1976). In the simplest case, activities can be performed independently from each other and their respective outputs are simply pooled in the end to yield the overall output (“pooled interdependence”). In this case, no coordination is required while workers are performing their tasks. In other cases, activities are interdependent in a sequential manner, i.e., the output of one activity serves as the input into another (“sequential interdependence”). In this case, coordination is required only as workers hand off work outputs across stages of the production process. Third, “reciprocal interdependence” describes tasks that depend on each other such that work flows back-and-forth between workers, requiring a significant amount of coordination and mutual adjustment. Finally, some activities

need to be performed simultaneously, without a measurable temporal lapse in the flow of work (what could be called “simultaneous interdependence”). Reciprocal and especially simultaneous interdependencies between activities imply a high need for coordination between workers performing the respective activities, resulting in high coordination costs.

In the context of knowledge production, coordination costs may not only depend on the frequency and sequencing of interactions, but also on the ease of communicating and integrating intermediate knowledge outputs across individuals. Intermediate knowledge is more easily transferred if it can be codified at low cost, while communication and integration across different individuals is more difficult if knowledge is tacit (Polanyi, 1966; Osterloh & Frey, 2000). As such, even for a given type of interdependence between the various stages of the research process, the costs of distributing activities across multiple individuals may depend on the tacit versus codified nature of the intermediate knowledge output that is produced. Taken together, the coordination costs between two activities may depend on the frequency and timing of interactions as well as the tacit vs. explicit nature of intermediate knowledge outputs. The higher the coordination costs between two activities, the more advantageous it is to have both performed by the same individual rather than different individuals, possibly leading to positive correlations between two activities (ρ_{jl} in our framework).

Coordination costs may be important not just *across* different activities, but also *within* a given activity. In particular, teams may try to split an activity into different sub-activities and assign sub-activities to different members. Similar to our earlier discussion, the resulting coordination costs are likely to depend on the nature of the interdependence between sub-activities and on the tacit vs. explicit nature of the intermediate knowledge outputs. For example, if sub-activities exhibit reciprocal or simultaneous interdependence, distributing them among multiple individuals would result in high coordination costs, suggesting a low degree of “decomposability” of the activity (Simon, 1962; Von Hippel, 1990). Such an activity should be performed by few individuals rather than distributed across many, resulting in a higher degree of concentration in our framework. Conversely, if the results of sub-activities can easily be pooled to get the desired output, multiple individuals can work independently and in parallel. This discussion highlights an important point: While one can study division of labor within activities (i.e., by considering more fine-grained layers of sub-activities), it is useful to define division of labor with respect to a given set of activities at a pre-defined level of aggregation (the columns in Figure 1). Defining a particular level of analysis and the corresponding set of activities is also consistent with applied efforts to develop standard classifications of work activities and to document team members’ contributions (Allen et al., 2014). Indeed, such efforts provide the data for the following empirical part of the paper, which applies our conceptual framework to study the division of labor in scientific teams.

3 Data and Key Measures

3.1 Data

Our analysis draws on data from articles published in the journal PLOS ONE. This journal is the largest Open Access peer-reviewed journal and was started in 2006 by the Public Library of Science.⁴ The journal is currently ranked in the top quartile in the interdisciplinary sciences by ISI Web of Science. PLOS ONE has a strong reputation in the scientific community and a recent study published in *Science* highlights particularly the journal's rigorous and transparent peer review process (Bohannon, 2013).

Data from PLOS ONE are particularly appealing for two reasons. First, they allow us to gain insights into a broad range of scientific projects since articles vary considerably in terms of both fields and article impact. With respect to the latter, it is PLOS ONE's official policy to peer review papers only with respect to technical accuracy but to leave judgments regarding "importance" to the readers. This aspect is particularly useful for us because it mitigates concerns about selection bias; whereas publications in highly selective journals such as *Science* or *Nature* reflect work of only a small number of very successful research projects, our sample provides insights into a much broader set of projects and teams. Moreover, the considerable variation in article impact allows us to explore the relationship between division of labor and impact empirically. Second, PLOS ONE is a pioneer in requiring authors to disclose the contributions made by each team member (more details below).

We obtained data for 14,602 research articles published from February 2007 to September 2011.⁵ Since we are interested in the division of labor within teams, we dropped 233 single authored papers, 169 papers that did not disclose the contribution of one or more authors, 54 papers that did not use the standard classifications or listed only "other contributions", and 61 papers that did not list any authors as having "written" (since each paper needs to be written, the contribution statements of these papers are likely incomplete). We complement the information obtained from the articles with information on the Scopus citations received by each article until October 2014, available on the PLOS ONE website. In addition, we collected data on the quantity and quality of authors' prior publications using the Scopus database. We exclude from our analysis 940 papers that had at least one author who we could not match to the Scopus database; the records of all other authors were matched using the unique author identifier provided by Scopus.⁶ Finally, we exclude papers with more than 20 authors (N=150) since the organization of knowledge production may be qualitatively different in big science projects (see Bikard et

⁴ <https://en.wikipedia.org/wiki/PLOS>; <http://journals.plos.org/plosone/s/reviewer-guidelines>

⁵ We excluded the first 200 papers published in PLOS ONE to account for the community having to acquaint itself to the new journal and its processes. Including these papers does not change our results.

⁶ We hand-checked authors with more than 200 returned publications and dropped some cases where the Scopus matching seemed erroneous. For example, our tool returned 1101 publications for the five years prior to the focal PLOS publication for the very common name *Ying LIU* and 783 publications for *Lin XU*. We also dropped papers with a small number of individuals for whom Scopus returned publications that were more than 60 years old.

al., 2015) and since the small cell sizes make team-level analyses of very large teams difficult. Overall, we analyze data from 12,995 papers that list 83,727 authors.

3.2 Key measures

Table 1 shows summary statistics for all individual-, activity-, and team-level variables. In the following, we discuss key measures of contributions and division of labor. We introduce additional variables in the context of our analyses below.

Types of contributions. Upon submission of a manuscript, PLOS ONE asks authors to specify the particular contributions made by each author. To do so, the journal offers a form with five pre-defined types of contributions: (1) conceived and designed the study (*i_conceived*) (2) performed the experiments (*i_performed*), (3) contributed materials, such as physical inputs/reagents/analysis tools (*i_materials*), (4) analyzed the data (*i_analyzed*), and (5) wrote the paper (*i_wrote*). For these 5 standard contributions, authors enter the respective co-authors' initials into the corresponding box and our variables capture whether or not a particular individual *i* made this contribution. For non-standard contributions, a free-text field “other” allows authors to indicate additional contributions and which individuals have made them. We create a dummy variable indicating whether a particular individual was listed as having made some other contribution (*i_other*).⁷

We recognize that listed contributions may be imperfect measures of the activities performed by the individuals who participated in a project. In particular, our measure does not capture work done by “ghost authors” who made significant contributions but are not listed as authors on the paper, although the share of such individuals in teams tends to be very small (Haeussler & Sauermann, 2013; Lissoni et al., 2013). Relatedly, the listing of author contributions may reflect not only objective contributions but also a social process of negotiation among team members, with more powerful or accomplished team members potentially negotiating to be listed as having made contributions they did not actually make. The latter concern is partly mitigated by the fact that being listed as having made particular contributions confers not only credit but also responsibility for low-quality work, mistakes or misconduct (Rennie et al., 1997). To further mitigate this concern, we will include a number of individual-level control variables in our regressions. Finally, the contribution measures are dichotomous, informing us that team members have contributed above a certain minimum threshold to be listed under a particular activity, but providing little insight into the extent of their contributions beyond that threshold. Despite their limitations, our measures have key advantages over available alternatives. Most obviously, they allow us to examine division of labor in a large sample of projects, complementing prior qualitative work using small numbers of cases

⁷ For example, the “other” contributions included items such as “developed design of simulation”, “critically revised the method” or “performed subject recruitment”.

(Owen-Smith, 2001). By using pre-defined categories, we obtain measures that are easily compared across teams, while relying on the scientists themselves (rather than less knowledgeable coders) to decide which categories best fit the contributions made by the various team members. Finally, while information about author contributions can also be obtained through surveys (Haeussler & Sauermann, 2013; Shibayama et al., 2015), individuals may overestimate their contributions to a team effort (Kamo, 2000; Ivaniš et al., 2011). The contributions listed on PLOS papers should be less affected by such biases to the extent that they reflect a consensus assessment of team members, all of whom realize that giving “too much” credit to another team member may reduce the credit allocated to them.⁸

Measures of division of labor. Guided by our conceptual discussion, we capture division of labor using a number of complementary measures at the level of individuals and of activities.

At the individual level, we first count the number of activities performed by a given author (*i_countcontributions*). A second, relative measure divides this count by the total number of types of contributions listed on the paper (*i_sharecontributions*). This ratio reflects what share of the up to 6 listed types of contributions a particular author performed. This variable equals 1 in the extreme case that a team member performs all the activities that are listed on the paper (i.e., no specialization). The measure is lowest (0.167) for individuals who perform only one of six listed activities. Using this relative measure, we also categorize individuals by whether they are “specialists” (team members who are involved in $\leq 20\%$ of contributions), “generalists” (team members who are involved in $> 60\%$ of contributions), or individuals with medium levels of specialization, resulting in the measures *i_specialist*, *i_generalist*, and *i_mediumspecialization*.

We aggregate these individual measures to the team level by computing the average number and share of contributions across all team members, resulting in *ti_avgcountcontributions* and *ti_avgsharecontributions*. Similarly, we compute for each team the share of specialists, generalists and individuals with medium specialization, resulting in the measures *ti_shareofspecialists*, *ti_shareofgeneralists*, and *ti_shareofmediumspecialization*.

At the level of the activity, we count the number of authors that performed the activity resulting in the measures *a_countconceived*, *a_countperformed*, *a_countmaterials*, *a_countanalyzed*, *a_countwrote*, and *a_countother*. We divide these counts by the total number of authors on the paper to obtain *a_shareconceived*, *a_shareperformed*, *a_sharematerials*, *a_shareanalyzed*, *a_sharewrote*, and *a_shareother*. We average these measures across activities to obtain two team-level measures *ta_avgcountofauthors* and *ta_avgshareofauthors*.

⁸ PLOS ONE encourages authors and researchers to correct errors in published papers and offers a simple process for doing so. Out of roughly 98,000 articles published by April 21, 2014, 3,367 were corrections. Of these corrections, 147 made corrections to author contributions or author order. Thus, authors do not hesitate to make corrections if necessary but corrections to authorship are very rare, presumably reflecting that publicly stated author contributions are agreed upon before a paper is published.

The count and share-based measures are highly correlated and provide very similar results. As such, we provide some descriptive insights using both count and share measures, but will focus our detailed analyses on the share measures. Moreover, the two measures *ti_avgshareofcontributions* and *ta_avgshareofauthors* are identical, consistent with our conceptual discussion. As such, we summarize division of labor at the team level using just one of these measures, *ti_avgshareofcontributions*.

Team size. *t_teamsize* is the count of the number of co-authors on the paper.

--- Table 1 about here ---

4 Characterizing division of labor in teams

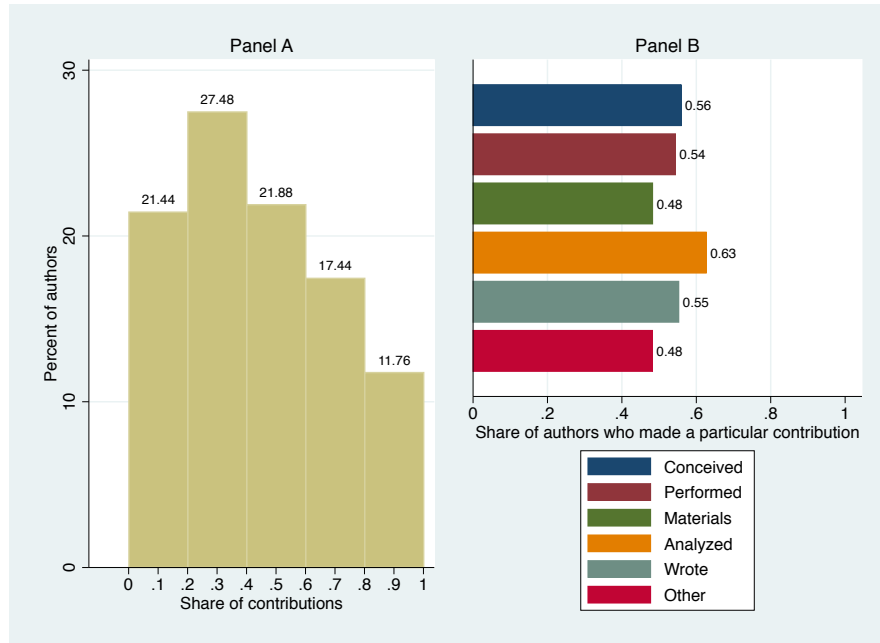
4.1 Individual-level and activity-level perspectives

Table 1 shows that the average team has 6.55 team members; 86.32% of teams have 10 or fewer members and 97.45% of teams have 15 or fewer members. The average project lists 4.8 out of 6 possible activities. Conception, performing the experiment, analysis, and writing are part of virtually every paper in the sample. The share of papers that list contributions of materials/data is somewhat lower (70%). Only 18% of papers list some “other” contribution, suggesting that the 5 pre-defined contributions are sufficient to describe the roles of most authors.

As per our conceptual discussion, we can first examine division of labor from the perspective of individuals. Table 1 shows that the average author performs 2.46 different activities. Using the relative measure (*i_avgshareofcontributions*), the average author performs 51% of the activities listed on his/her paper. Panel A in Figure 2 plots the distribution of this measure, showing considerable heterogeneity across individuals: Roughly 21% of authors perform 20% or less of all listed contributions (“specialists”), while almost 30% perform more than 60% of all listed contributions (“generalists”).

Activity-level measures summarized in Table 1 show that the average activity was performed by 3.3 individuals, or 56% of all listed team members, conditional upon the activity being listed on a paper. Panel B in Figure 2 reveals some heterogeneity across activities in the degree to which they are distributed among many team members vs. concentrated among fewer: The share of team members performing an activity ranges from 48% (share of authors who contribute materials or made an “other” contribution if such a contribution was listed) to 63% (share of authors who analyzed data).

Figure 2: Individual and activity level measures of division of labor



Note: Panel A shows the distribution of the share of contributions performed by a team member ($i_avgshareofcontributions$). Panel B shows the average share of team members performing a particular activity, conditional upon that activity being listed on the paper ($a_shareauthors$).

4.2 Integrating individual and activity level perspectives

Looking across both individuals and activities allows us to examine whether certain activities tend to be performed by specialized individuals while others tend to be performed by generalists. For that purpose, we focus on the authors listed as having performed a particular activity and compute the share of these authors who are specialists ($i_sharecontributions \leq 0.2$, Figure 3, panel A), have medium specialization ($i_sharecontributions > 0.2$ but ≤ 0.6 , panel B) and low specialization ($i_sharecontributions > 0.6$, panel C). Figure 3 shows that *performed* and *materials* (as well as *other*) have the highest share of highly specialized team members and the lowest share of generalist team members. In contrast, *conceived* and *wrote* have the smallest shares of specialists and the largest share of generalists, perhaps suggesting that these particular activities benefit less from specialization and exhibit important interdependencies with other activities.

We can explore potential interdependencies between activities more explicitly by examining which activities tend to be performed jointly by the same individuals. To do so, we use the individual level observations and regress the indicator for a focal activity (i.e., i_wrote) on the set of the 5 remaining ones. Since we are interested in how activities are correlated within a given team, we estimate these regressions using linear probability models (LPM) with paper fixed effects.

The paper fixed effects control for unobserved heterogeneity at the level of the project (e.g., the nature of the project). In addition, we include a number of individual level controls. First, we code a number of variables based on the affiliations listed for each author. We measure the reputation of an author's listed institution using the variable *i_institutionrank* based on the 2012 Academic Ranking of World Top 500 Universities (the so-called Shanghai ranking). The variable is 1 if an author's institution belongs to the Top 20 universities, 2 for Top 21-50, 3 for Top 51-100, 4 for Top 101-200, 5 for Top 201-300, 6 for Top 301-400, 7 for Top 401-500 and 8 for non-listed universities. We used the highest ranked institution for authors with more than one affiliation. The indicator variable *i_developingcountry* is one if an author has at least one affiliation in a developing country and zero otherwise. In addition to information taken from the PLOS articles, we obtained data on authors' prior publications using the Scopus database. We use the number of publications over the five years prior to the focal PLOS article as our measure of the quantity of prior publications (*i_priorpubs_quantity*). We use the average yearly number of citations to these articles (dividing total yearly citation counts by the total number of publications) as a proxy for the quality of prior publications (*i_priorpubs_quality*). We estimate *i_professionalage* as the difference between the year of the PLOS paper and the year of the first publication. Including these measures of authors' prior publications and professional age is useful to account for the possibility that the division of labor in teams reflects not only efficiency considerations (emphasized in our conceptual discussion) but also social mechanisms. For example, more senior or more accomplished team members may choose to work on activities they prefer and delegate other activities to more junior team members.

Model 1 in Table 2 uses as dependent variable the dummy indicating whether a team member has contributed by writing the paper (*i_wrote*). We find a strong positive relationship with *conceived* and *analyzed*, consistent with the notion that writing involves the integration of conceptual ideas and empirical results and that there are interdependencies between these three activities that make it beneficial for the same team members to be engaged in all three. Model 2 uses as dependent variable whether an individual was involved in data analysis. The strongest relationship emerges again with writing. In addition, data analysis is correlated with performing the experiment, perhaps reflecting reciprocal interdependencies between these two activities (Latour & Woolgar, 1979; Owen-Smith, 2001). In contrast, individuals who contributed materials are less likely to also have analyzed. Model 3 focuses on the predictors of having provided materials and shows that it has a negative relationship with all other activities. The negative coefficient is largest for performed, perhaps indicating that performing experiments and contributing materials (including data) are alternative ways to obtain data and that a given individual will do either one but not both. Model 4 reinforces this finding by showing a strong negative relationship between performed and materials, while also showing a significant positive

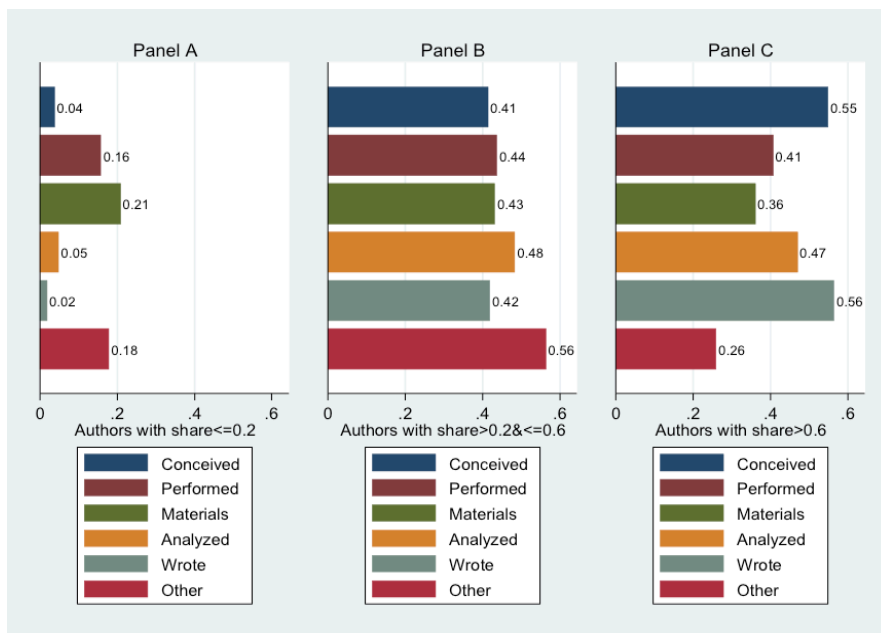
relationship between performed and analyzed. Finally, Models 5 and 6 examine which activities predict that a team member has conceived or has conducted an “other” activity and are consistent with the earlier results.

Although our focus is on the relationships between different types of contributions, several control variables also have significant coefficients. For example, professional age is positively related to writing, conceiving, and providing materials, while it is negatively related to performing the experiment or analyzing data. While a deeper analysis of which particular team members are engaged in which activities is beyond the scope of this paper, this result is consistent with prior work on the roles of junior versus senior lab members (Owen-Smith, 2001; Shibayama et al., 2015).

Overall, these regressions suggest systematic patterns in the relationships among activities. Individuals who write the paper tend to also be engaged in analysis and conception, while individuals who perform the experiment are likely to also be involved in data analysis. The provision of materials tends to be relatively independent.⁹

--- Table 2 here ---

Figure 3: Degree of specialization by type of activity



Note: Share of team members who performed a particular activity and have a high level of specialization (panel A), medium specialization (panel B), and low specialization (panel C).

⁹ An alternative empirical approach would be to perform a factor analysis. Using this approach, one factor with eigenvalue > 1 emerges, with the largest loadings for *i_conceived*, *i_wrote*, and *i_analyzed*. Two smaller factors have eigenvalues < 1, one combining *i_performed* and *i_analyzed*, and the other including only *i_materials*. While these results are consistent with our regression approach, the latter provides more detailed insights into the relationships between each pair of activities.

4.3 Division of labor and team size

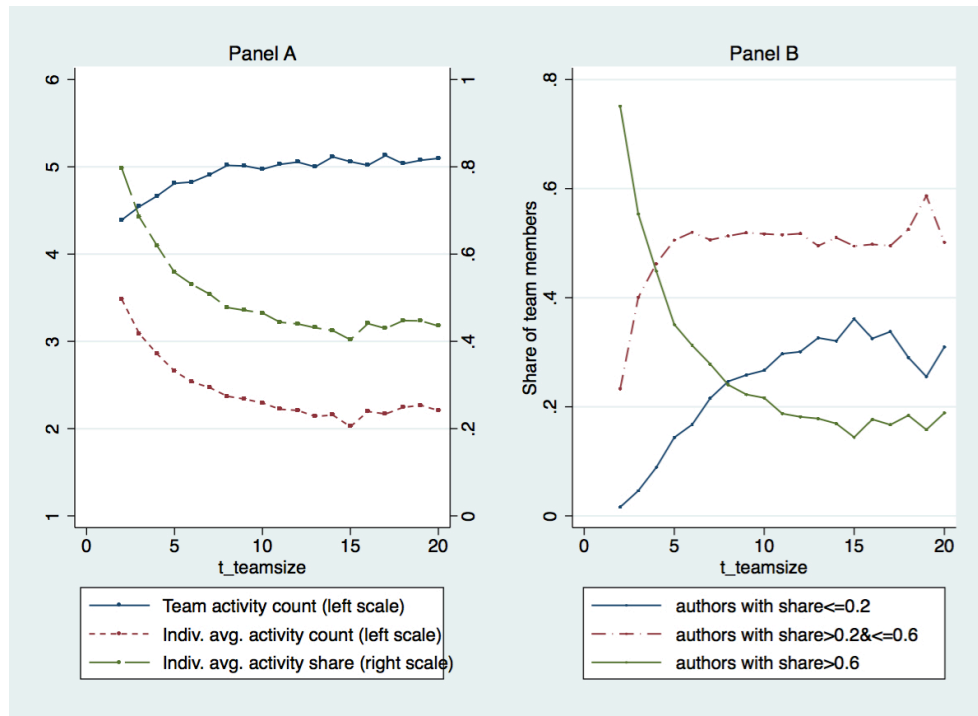
Prior literature suggests that division of labor may depend on the total volume of work and the size of the organization (Smith, 1776; Stigler, 1951; Becker & Murphy, 1992; Jones, 2009). As such, we now use our framework to explore how the division of labor differs across teams of different size.

4.3.1 Individual level perspective

Panel A in Figure 4 plots $ti_avgcountcontributions$ and $ti_avgsharecontributions$ against the size of the team, allowing us to examine the relationship between team size and team members' degree of specialization. For reference, we also plot the average number of contributions listed on the paper, which increases from roughly 4.5 for very small teams to roughly 5 for larger teams.

Consistent with prior theory, Panel A shows that team members in larger teams tend to be more specialized: while the average member in teams of 2 performs roughly 3.5 activities (80% of all listed contributions), that number decreases to roughly 2 activities (roughly 43% of listed contributions) in teams of 14 or more. Despite this tendency towards specialization in larger teams, however, the measures of specialization level off well before reaching the extreme (i.e., a single activity).

Figure 4: Individual level measures and team size



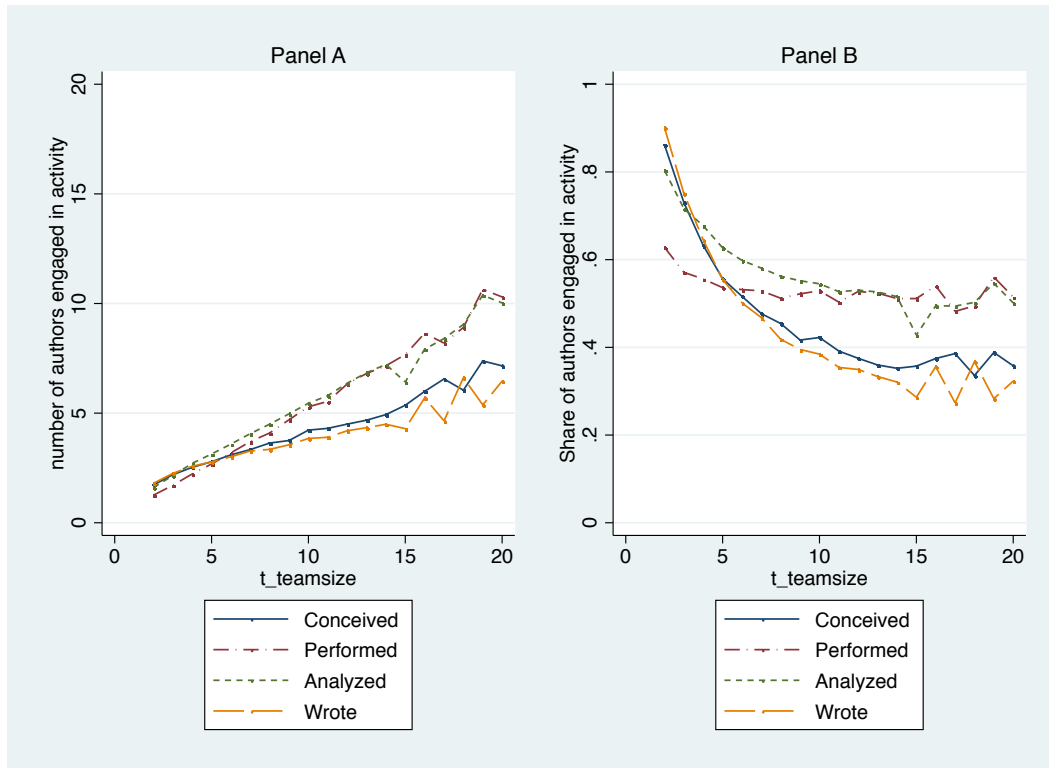
Note: Average share and count of activities per team member, and count of listed activities by team size (Panel A). Share of specialists, intermediate types, and generalists by team size (Panel B).

To explore heterogeneity across team members, Panel B plots the shares of specialists, intermediate types, and generalists in a team. The share of specialists increase sharply with team size but then stabilizes at a team size of roughly 15, reaching around 30%. The share of generalists decreases until about a teamsize of 10 but then remains quite stable at roughly 18%. Thus, while larger teams employ higher division of labor, most individuals do not specialize perfectly. Moreover, even large teams have generalists who perform a broad range of activities, perhaps because such individuals help teams overcome the coordination and integration challenges associated with higher division of labor.

4.3.2 Activity level perspective

Switching from the individual to the activity level perspective, we explore how activities differ with respect to their distributed vs. concentrated nature across teams of different sizes. Panel A in Figure 5 plots the number of team members who perform a given activity by team size, conditional upon an activity being listed on the paper. We find that the number of individuals performing a given activity increases with team size. Conversely, Panel B shows that the *share* of individuals engaged in a particular activity decreases, i.e., activities become more concentrated.

Figure 5: Activity level measures and team size



Note: Counts of team members performing each activity by team size (Panel A). Shares of team members performing each activity by team size (Panel B).

Considering differences across activities, we find that concentration increases less for *performed* and *analyzed* than for *conceived* and *wrote*. For example, the share of team members involved in writing drops from 90% in teams of 2 to 32% in teams of 20. The share of team members who *performed* decreases less strongly from 63% to 51%. This leads to an interesting inversion: writing and conceptualization tend to be more distributed than empirical activities in small teams, but empirical activities tend to be more distributed than writing and conceptualization in large teams. One potential explanation for the latter result is that conceptual activities require only a relatively fixed amount of work regardless of project size such that there is less need for a large number of team members to get involved. Alternatively, conceptual activities may have a lower degree of “decomposability” than empirical activities, i.e., it is more difficult to split conceptual activities in discrete subtasks that can be assigned to different team members (Von Hippel, 1990).

4.3.3 Regressions

Regression analysis allows us to explore the role of team size while controlling for a number of potentially confounding variables (Table 3). To control for differences in the nature of research and of resource availability, we include the indicator variable *t_funding_basic* that equals one if the paper acknowledges funding from a governmental basic research funding agency such as the National Science Foundation, National Institute of Health, German Research Foundation, or the World Health Organization. The variable *t_funding_industry* equals one if the paper acknowledges funding from a for-profit organization. The variable *t_funding_other* equals one if a paper acknowledges funding from another source. We further control for differences in the nature of research by including fixed effects for 42 *fields* (+1 “other”) based on field classifications listed on the article. Note that each paper can be classified into multiple fields, and the average number of field classifications is 2.49.

We also include a number of variables to control for differences in the composition and location of teams. The measure *t_affiliations* counts the number of unique author affiliations listed on the paper. The dummy *t_country_US* equals 1 if the first author’s main affiliation is in the US, and *t_country_developing* equals 1 if the first author’s main affiliation is in a developing country (other countries is the omitted category).¹⁰ We code the variable *t_firm* as 1 if at least one of the author affiliations is with a firm.¹¹ Finally, we include as additional article level controls the number of pages

¹⁰ We use the affiliation of the first author since this person likely contributed most to the project and his/her first listed affiliation is clearly his/her main affiliation. For other authors, the first listed affiliation does not have to be the main affiliation since PLOS ONE uses one set of affiliation identifiers in running order. As such, an affiliation that appears for an author early in the author list will appear first for a later author even if it is not the later author’s main affiliation.

¹¹ We searched for terms such as “corporation”, “inc”, and “S.A.”. We also manually checked author affiliations to identify commonly occurring firm names such as Pfizer or Roche.

(*t_pages*), the publication date (*t_publication_date*), and the number of listed research activities (up to 6, *t_totalactivitieslisted*).

Model 1 uses *ti_avgsharecontributions*, which is our most aggregated measure of division of labor. Consistent with Figure 4, we find a significant negative coefficient of team size, suggesting that in larger teams, team members perform a smaller share of all contributions, i.e., they are more specialized. Recall that this measure is equivalent to *ta_avgshareofmembers*. As such, this regression also shows that as team size increases, activities tend to be performed by a smaller share of individuals – activities are more concentrated. The positive coefficient on team size squared suggests decreasing marginal effects, again consistent with Figure 4.

Models 2-4 provide a more nuanced view by exploring how team size relates to the share of specialists, generalists, or individuals with medium levels of specialization. We find that team size has strong negative association with the share of generalists, and a positive relationship with both specialists and intermediate types.

Finally, models 5-10 focus on the activity level of analysis, exploring how team size is related to the share of members performing each of the six activities. These regressions are conditional upon a contribution being listed, i.e., we drop papers that do not list the focal contribution. Consistent with Panel B in Fig. 5, we find that team size has a negative and convex relationship with all 6 measures. However, the size of the coefficient of team size differs across activities, with the largest negative effect for *a_shareconceived* and *a_sharewrote* and a much weaker coefficient for *a_shareperformed*.¹²

Taken together, these regressions show that the major trends visible in Figures 4 and 5 hold even when we examine the relationship between team size and division of labor in a multivariate context: Division of labor increases with team size, as reflected in an increase in the share of specialists and a decrease in the share of generalists, as well as an increasing concentration of activities among smaller shares of team members.

--- Table 3 here ---

5 Differences in division of labor across fields and types of projects

The prior sections examined levels and patterns of division of labor across a broad sample of teams, illustrating the use of individual and activity level measures derived from our conceptual framework. For organizational scholars, an important question is whether and how division of labor differs across different types of projects or institutional contexts (Hagstrom, 1964; Shibayama et al., 2015). We now provide some initial descriptive insights into this question by exploring differences

¹² If we use the counts of team members rather than the shares of team members performing particular activities as dependent variables, team size has a significant positive coefficient, consistent with Figure 5.

between papers in novel versus established fields and in interdisciplinary vs. single-disciplinary projects. While we will not be able to explain any observed differences, we hope that our insights can stimulate future research on underlying mechanisms.

Our general approach is to estimate a set of regressions with the measures of division of labor as dependent variables and with our focal project characteristics as independent variables (Table 4). All regressions control for other project characteristics, including a series of dummy variables for team size.

5.1 Novelty of the field

To obtain a proxy for the age of a field, we identified for each of the 42 detailed fields the main professional society or association and determined the year of its founding. We then classified fields as “novel” if the society/association was founded after 1970. We classified papers according to the youngest listed field, resulting in 20.86% of papers classified as in a novel field and 79.14% as in an established field (*t_field_novel*).

Model 1 in Table 4 shows that in novel fields, team members engage in a smaller share of listed activities, i.e., they are more specialized. Similarly, models 2-4 show that teams in novel fields have a significantly smaller share of generalists and a larger share of specialists (see Fig. 6, Panel A). Activity level regressions (model 5-10) reveal that the greater division of labor reflects primarily that a smaller share of team members is involved in performing experiments, although a somewhat larger share of members is involved in writing (Fig. 6, Panel B). One potential explanation for the former result is that newer fields require larger investments into learning new empirical methods. As per our conceptual discussion, such fixed costs would make it beneficial to allocate work to a smaller number of (more specialized) individuals. We can also relate these results to the model developed by Jones (2009), who suggests that a larger stock of total knowledge in a field requires that scientists make larger investments to reach the knowledge frontier, increasing the benefits from specialization and collaboration. Interpreted in light of this model, the observed higher division of labor in novel fields suggests that new fields tend to build upon established fields rather than replacing them, thus relying on a larger total stock of knowledge and providing greater potential for benefits from specialization.¹³

Finally, we explore whether novel and established fields also differ with respect to the correlations between different activities. Towards this end, we replicate the regressions reported in Table 2 but include interactions between novelty and work activities. Table 5 shows that in novel fields, there is a weaker association between conceiving and writing, between conceiving and materials, and between

¹³ We chose 1970 as the cut-off to define novel fields since from then on genetics united with biotechnology (e.g., recombinant DNA was discovered in 1973). Among others, novel fields according to our classification include biotechnology (1976), virology (1981) and computational biology (1987). If we use as the cutoff the median age of all fields (1964), we find that besides the coefficient for *ta_shareperformed* also the coefficient for *ta_shareconceived*, *ta_shareanalyzed* and *ta_shareother* suggest that these activities are more concentrated in novel projects.

conceiving and other contributions, suggesting that conceiving tends to be a more independent contribution than in established fields. On the other hand, there is a stronger correlation between performing and materials, suggesting that providing materials is less independent in novel fields.

5.2 Interdisciplinarity of the project

We next explore whether division of labor is different in interdisciplinary projects compared to projects that are firmly placed in a single field. To proxy for interdisciplinarity, we count the number of detailed field classifications listed on the paper and form three categories indicating whether a paper was classified in only one field (19.63%), two or three fields (64.85%), or 4 or more fields (15.51%).

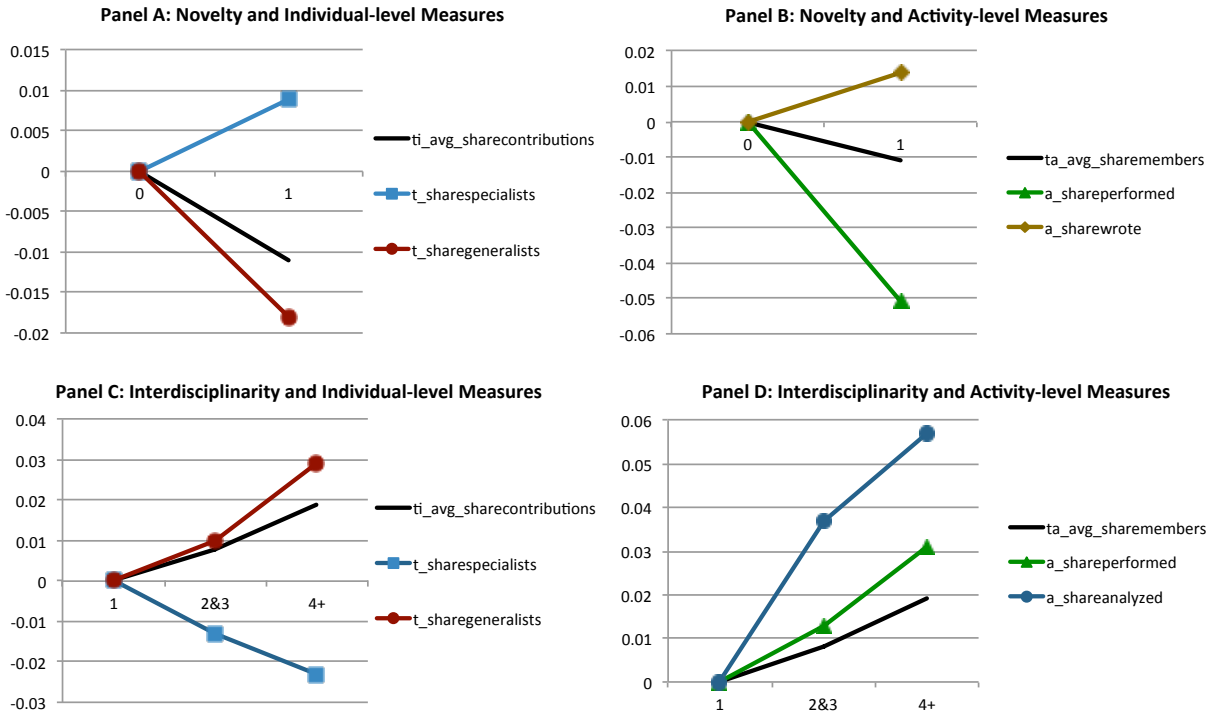
Model 1 in Table 4 shows that division of labor is lower in multidisciplinary fields (model 1), reflecting both a higher number of generalists and a lower number of specialists (models 2-4; Fig. 6 Panel C). Taking an activity-level perspective, models 5-10 show that this lower division of labor reflects primarily the more distributed nature of empirical activities: interdisciplinarity projects have a significantly higher *a_shareperformed* as well as *a_shareanalyzed* (Fig. 6, Panel D). An intuitive interpretation is that while team members in interdisciplinary projects may be more specialized in terms of their field background, they integrate these different perspectives by collaborating more closely on the same activities. More specifically, interdisciplinary projects may draw on a broader set of (field-specific) empirical techniques, thus limiting teams' ability to concentrate empirical work among a smaller set of individuals specializing in empirical work. This interpretation raises the more general interesting point that patterns of division of labor with respect to activities may be very different from individuals' specialization in terms of knowledge domains. We will return to this issue in the general discussion.

Models 7-12 in Table 5 provide additional insights by exploring whether interdisciplinary projects exhibit different correlations between activities. We find that individuals who provided materials are also more likely to write the paper compared to single-discipline fields. At the same time, individuals who performed the experiment are less likely to provide materials and to analyze data.

Taken together, our exploratory analyses suggest that the division of labor differs significantly between fields and types of projects. Moreover, while such differences can be observed using aggregate team-level measures, more detailed measures at the level of individuals (e.g., share of specialists vs. generalists) and of activities (e.g., share of members writing versus share of members performing experiments) provide additional insights and can even show contrasting results (Fig. 6). While our goal was to simply describe potential differences in the division of labor, the observed differences across fields and types of projects call for future work on underlying drivers.

--- Tables 4 and 5 here ---

Figure 6: Differences in division of labor across fields and types of projects



Note: Regression coefficients based on OLS regression reported in Table 4. Only significant coefficients shown. Panels A and B focus on novelty as the dependent variable (0=established, 1= novel field). Panels C and D focus on interdisciplinarity (1 field, 2&3 fields, 4 or more fields).

6 Division of labor and the quality of scientific output

In organizational theory and economics, the division of labor is seen as a key mechanism to increase efficiency and performance. In a final set of analyses, we therefore explore the relationship between division of labor and the quality of scientific output. Of course, teams can pursue a range of different outcomes and our empirical analysis will not address the endogeneity of team size and division of labor. As such, our primary goal is to demonstrate how our conceptual framework, combined with new data sources such as disclosures of contributions, can help researchers explore the relationships between organizational features of teams and the output they produce.

We will proxy for the quality of scientific output using (logged) Scopus citations received by our focal papers. Since citations take time to accumulate, all regressions include dummies for each month of publication and we also include a range of other control variables such as article characteristics and the average citation rate of co-authors' prior publications. Models 1 to 4 in Table 6 include 42 (+1 other) field dummies; Models 5 to 8 instead use our measures of the novelty of the field and of interdisciplinarity.

Models 1 and 5 show the results without controls for the size of the team. We observe that higher division of labor is associated with larger citation impact, as reflected in the negative coefficient on

ti_avgsharecontributions. However, both division of labor and impact may reflect underlying differences in the size of the project. As such, models 2 and 6 flexibly control for team size using dummy variables. *ti_avgsharecontributions* now has a positive coefficient, indicating that for teams of a given size, higher division of labor is associated with lower citation impact.

Models 3 and 6 provide more detailed insights by including not the aggregate measure of division of labor, but the shares of generalists and of individuals with intermediate levels of specialization (specialists are the reference category and all three shares sum to 100%). We observe that a higher share of generalists tends to be associated with a higher citation impact but this coefficient is only significant in Model 6, which includes controls for the age of the field and interdisciplinarity of the project. Models 4 and 8 include the activity-level measures indicating what share of team members is engaged in a given activity. One coefficient stands out in both models: teams in which a larger share of members is involved in writing produce papers with significantly higher citation impact. This result may be due to selection, i.e. that more authors try to get involved in writing if the project seems particularly promising, but may also reflect that collaborative writing results in more interactions and feedback among co-authors, resulting in higher quality output.¹⁴

To summarize, we find that, controlling for team size, higher division of labor is associated with lower citation impact. Further analyses using more detailed measures of division of labor suggest that this result reflects higher citations for teams with more generalists, and particularly teams that involve a larger share of their members in writing. This result should not be interpreted as causal since we cannot control for potentially important factors such as unobserved heterogeneity with respect to the nature of the research teams are performing. Moreover, even if this effect were causal, one should keep in mind that teams do not necessarily focus on maximizing the citation impact of papers. Some teams may focus on speed rather than impact, while other teams may focus on minimizing costs, e.g., by employing lower-skilled and potentially more specialized members (Freeman et al., 2001; Stephan, 2012). Finally, some teams may pursue not only scientific productivity but also the training of team members (Hackett, 1990; Shibayama et al., 2015). Nevertheless, the analysis in this section illustrates how our framework and measures can be used to illuminate the relationships between division of labor and such a broader range of outcomes.

¹⁴ Given our finding of significant differences in division of labor in novel fields and in interdisciplinary teams, a final question is whether the relationships between division of labor and impact may also be contingent on these factors. In an auxiliary analysis we address this question by interacting *t_avgsharecontributions* with the measures of novelty and interdisciplinarity but find no significant interactions.

7 Discussion

Teams play a central role in many organizations and have also become increasingly important in knowledge production (Wuchty et al., 2007; Stephan, 2012; Cummings & Kiesler, 2014). However, little is known about how work is divided and distributed among knowledge workers. Conceptualizing research as a process that involves a number of distinct activities such as conceptualization, data collection, and analysis, we developed a conceptual framework to analyze division of labor in teams using multiple perspectives. Focusing on individual team members, the first perspective provides insight into individuals' levels of specialization. Focusing on particular activities, the second perspective provides insights into the degree to which activities are distributed across multiple team members vs. concentrated among a few. Considering both individuals and activities, the third perspective provides insights into relationships between activities, i.e., which activities tend to be performed together by the same individuals, and which activities tend to be performed independently.

Drawing on this framework, we then explore the division of labor in scientific teams based on data from over 12,000 articles disclosing the contributions of individual authors. In addition to providing nuanced descriptive results that should be of interest in their own right, our empirical analysis also highlight an important more general point: while division of labor can be characterized using aggregate measures at the level of the team, there is significant heterogeneity across individual team members and different types of activities. As such, while team-level measures may be useful for some purposes, the higher level of granularity afforded by individual and activity level measures is likely to provide a richer basis for future research on the drivers and consequences of division of labor in teams.

We make several contributions to the organizational literature, which has devoted significant attention to teams. Among others, scholars have studied social networks among team members, antecedents and consequences of team diversity, optimal incentive provision, and mechanisms that may overcome coordination challenges (Becker & Murphy, 1992; Postrel, 2002; Hamilton et al., 2003; Majchrzak et al., 2012). While much of this prior work rests on the premise that team members perform different parts of the overall task, our conceptual and empirical understanding of this division of labor itself is limited. We contribute to this literature by offering a conceptual framework that systematically considers division of labor in teams from complementary perspectives and suggests a number of measures at different levels of analysis. This framework may provide a useful tool for analyzing division of labor in a variety of contexts where production processes can be conceptualized as involving a number of functional activities. Indeed, the framework may be useful even for researchers who wish to focus on team members' knowledge rather than functional activities (Singh & Fleming, 2010; Majchrzak et al., 2012; Teodoridis, 2013). For example, such an application could explore the degree to which members are specialized with respect to their knowledge domains, the extent to which a team's expertise in

particular domains is concentrated or distributed among different team members, and which particular domains are covered jointly by the same individuals versus covered by distinct sets of individuals.

In addition to this conceptual contribution, we provide novel empirical insights into patterns of division of labor, drawing on a new type of data that is likely to become increasingly available in future years. We suggest that such data and the various measures suggested by our framework may prove valuable for organizational research more generally by providing a toolkit and empirical setting that may allow researchers to study team processes at a relatively large scale (see Puranam, 2012).

Our study also contributes more specifically to the literature on scientific teams (Gittelman, 2007; Singh & Fleming, 2010; Gruber et al., 2013; Teodoridis, 2013; Bikard et al., 2015). Even though the scientific results of teamwork are often publicly disclosed, how these results are produced tends to remain hidden from outside observers, increasing the value of new data sources that provide insights into these underlying team processes. We present such a data source and draw on our conceptual framework to provide novel descriptive insights into patterns of division of labor in scientific teams. In doing so, we uncover striking differences in the division of labor across types of projects, i.e., a higher division of labor in novel versus established fields and lower division of labor in interdisciplinary versus single-disciplinary fields. While we demonstrated how the framework can be useful in analyzing differences across fields at a given point in time, it may also be useful for future research on potential changes in the division of scientific labor that may result from broader trends such as the increasing role of capital intensive equipment, the diffusion of information technologies, or the standardization and automation of research procedures (Agrawal & Goldfarb, 2008; Stephan, 2012; Franzoni & Sauermaun, 2014).

Our results suggest a number of other interesting avenues for future research. First, our empirical analyses focused on describing patterns of division of labor and we made only limited inroads into understanding the drivers of these patterns. Our limited efforts at interpreting results largely drew on prior work explaining division of labor from an economic and efficiency oriented perspective, yet there are several other mechanisms that may also provide important explanations. Among others, teams may not only pursue efficiency in the production of scientific knowledge, but may also pursue the education of individual team members (Hackett, 1990; Shibayama et al., 2015). Similarly, division of labor may also reflect social processes that allocate tasks not based on efficiency but based on status and power. Disentangling the relative role of these mechanisms is a first important avenue for future research.

Second, while our framework highlighted heterogeneity across team members in terms of their functional roles, we did not explore which particular members perform which particular activities or which particular team members emerge as specialists versus generalists. Among others, roles may be allocated based on a number of individual characteristics such as experience, educational background, or

social status (Owen-Smith, 2001; Shibayama et al., 2015). We hope that our conceptual framework can facilitate future work on these important relationships.

Third, our analysis explored the organization of work in given teams, but team formation itself is likely an endogenous process. For example, team size may reflect organizers' expected benefits from division of labor as well as concerns that credit for scientific work has to be shared with other individuals (Bikard et al., 2015; Walsh & Lee, 2015). While abstracting from team formation should not affect the value of our descriptive results, future efforts to understand the drivers of the division of labor should take team formation into account. Considering endogenous team formation will be even more important for efforts to establish the causal links between division of labor and the quality or quantity of output.

Fourth, our conceptual framework and empirical analysis focused on a given team as the relevant unit of analysis, but division of labor may reach beyond teams. For example, collaboration in multiple teams may allow some team members to specialize in particular activities even if any given project does not have the required size. Although the strong empirical relationship between team size and division of labor is consistent with the view that the size of a given team is very important, future work could fruitfully explore individuals' broader research portfolios and the resulting division of labor both within and across teams.

Finally, it would be interesting to explore complementarities between the activity-based perspective taken in this paper and the view conceptualizing science as the recombination of knowledge (Simonton, 2003; Singh & Fleming, 2010; Teodoridis, 2013). Prior work suggests that the functional division of labor may be quite different from the partitioning of knowledge (Postrel, 2002; Takeishi, 2002), and it is important to understand how the two are related in the particular context of science. For example, our observation that interdisciplinary projects involve lower division of labor suggests the intriguing possibility that team members who are specialists in terms of fields or knowledge domains may sometimes be generalists in terms of functional activities. Given that knowledge production in teams typically involves multiple team members that perform different sets of activities drawing on different types of knowledge, an integrated perspective that considers all three dimensions – individuals, activities, and knowledge - may be a particularly fruitful avenue for future research.

Finally, our results may also be of interest for the scientific community and for policy makers. First, the observed patterns of division of labor raise the question how scientists can best be prepared to be productive members of scientific teams. While conventional views (and many current prize mechanisms) emphasize individual accomplishment and suggest that scientists should be trained to perform the full range of research activities, there may be benefits to training scientists more specifically for particular types of functions. The increasing demand for “data scientists” is just one example.

Second, we observe a significant number of individuals who performed only one activity in the project, yet common authorship guidelines typically require authors' involvement in a broader range of activities, including conceptualization or empirical work, as well as involvement in writing (ICMJE, 2010). While one interpretation of this discrepancy is that teams violate authorship standards by including too many authors, another interpretation is that authorship standards need to be revised to accommodate the increasing specialization of scientific work. The best approach may be to replace or complement the traditional authorship system with more informative systems that clearly indicate the particular contributions of all team members (Rennie et al., 1997; Allen et al., 2014). Of course, this is why an increasing number of journals require the disclosure of author contributions, providing social scientists with a rich data source to investigate the division of labor in collaborative knowledge production.

REFERENCES

- Agarwal, R., & Sonka, S. 2010. Different strokes for different folks: University programs that enable diverse career choices of young scientists. In G. Libecap (Ed.), *Spanning Boundaries and Disciplines: University Technology Commercialization in the Idea Age*, Vol. 21: 139-164: Emerald Group Publishing Limited.
- Agrawal, A., & Goldfarb, A. 2008. Restructuring research: communication costs and the democratization of university innovation. *The American Economic Review*, 98(4): 1578-1590.
- Allen, L., Scott, J., Brand, A., Hlava, M., & Altman, M. 2014. Publishing: Credit where credit is due. *Nature*, 508(7496): 312-313.
- Arora, A., Cohen, W. M., & Walsh, J. P. 2014. The Acquisition and Commercialization of Invention in American Manufacturing: Incidence and Impact, *NBER Working Paper #20264*.
- Becker, G. S., & Murphy, K. M. 1992. The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, 107(4): 1137-1160.
- Bercovitz, J., & Feldman, M. 2011. The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Research Policy*, 40(1): 81-93.
- Bikard, M., Murray, F., & Gans, J. 2015. Exploring tradeoffs in the organization of scientific work: Collaboration and scientific reward. *Management Science*, 61(7): 1473-1495.
- Bohannon, J. 2013. Who's afraid of peer review? *Science*, 342: 60-65.
- Cummings, J. N., & Kiesler, S. 2014. Organization theory and the changing nature of science. *Journal of Organization Design*, 3(3): 1-16.
- Dasgupta, P., & David, P. A. 1994. Toward a new economics of science. *Research Policy*, 23(5): 487-521.
- Franzoni, C., & Sauermaun, H. 2014. Crowd Science: The organization of scientific research in open collaborative projects. *Research Policy*, 43(1): 1-20.
- Freeman, R., Weinstein, E., Marincola, E., Rosenbaum, J., & Solomon, F. 2001. Competition and careers in biosciences. *Science*, 294(5550): 2293.
- Fuhrmann, C., Halme, D., O'Sullivan, P., & Lindstaedt, B. 2011. Improving graduate education to support a branching career pipeline: Recommendations based on a survey of doctoral students in the basic biomedical sciences. *CBE-Life Sciences Education*, 10(3): 239-249.
- Gans, J., & Murray, F. 2013. Credit history: The changing nature of scientific credit, *NBER Working Paper #19538*.
- Gibbs, J. P., & Poston, D. L. 1975. The division of labor: Conceptualization and related measures. *Social Forces*, 53(3): 468-476.
- Gittelman, M. 2007. Does geography matter for science-based firms? Epistemic communities and the geography of research and patenting in biotechnology. *Organization Science*, 18(4): 724.
- Gruber, M., Harhoff, D., & Hoisl, K. 2013. Knowledge recombination across technological boundaries: Scientists vs. engineers. *Management Science*, 59(4): 837-851.
- Hackett, E. J. 1990. Science as a vocation in the 1990s. *Journal of Higher Education*, 61(3): 241-279.
- Haeussler, C., & Sauermaun, H. 2013. Credit where credit is due? The impact of project contributions and social factors on authorship and inventorship. *Research Policy*, 42(3): 688-703.
- Hagstrom, W. O. 1964. Traditional and modern forms of scientific teamwork. *Administrative Science Quarterly*: 241-263.
- Hamilton, B. H., Nickerson, J. A., & Owan, H. 2003. Team incentives and worker heterogeneity: An empirical analysis of the impact of teams on productivity and participation. *Journal of Political Economy*, 111(3): 465-497.
- ICMJE. 2010. Uniform requirements for manuscripts submitted to biomedical journals: Ethical considerations in the conduct and reporting of research: Authorship and Contributorship, Vol. 2010.

- Ivaniš, A., Hren, D., Marušić, M., & Marušić, A. 2011. Less work, less respect: authors' perceived importance of research contributions and their declared contributions to research articles. *PLoS ONE*, 6(6): e20206.
- Jones, B. 2009. The burden of knowledge and the “death of the renaissance man”: Is innovation getting harder? *Review of Economic Studies*, 76(1): 283-317.
- Jones, B. F., & Weinberg, B. A. 2011. Age dynamics in scientific creativity. *Proceedings of the National Academy of Sciences*, 108(47): 18910-18914.
- Kamo, Y. 2000. “He Said, She Said”: Assessing Discrepancies in Husbands' and Wives' Reports on the Division of Household Labor. *Social Science Research*, 29(4): 459-476.
- Knorr-Cetina, K. 1999. *Epistemic Cultures: How the Sciences Make Knowledge*. Cambridge, MA: Harvard University Press.
- Latour, B., & Woolgar, S. 1979. *Laboratory Life: The Social Construction of Scientific Facts*. Beverly Hills: Sage.
- Lissoni, F., Montobbio, F., & Zirulia, L. 2013. Inventorship and authorship as attribution rights: An enquiry into the economics of scientific credit. *Journal of Economic Behavior & Organization*, 95: 49-69.
- Majchrzak, A., More, P. H., & Faraj, S. 2012. Transcending knowledge differences in cross-functional teams. *Organization Science*, 23(4): 951-970.
- Nielsen, M. 2011. *Reinventing Discovery: The New Era of Networked Science*: Princeton University Press.
- Osterloh, M., & Frey, B. S. 2000. Motivation, knowledge transfer, and organizational forms. *Organization Science*, 11(5): 538-550.
- Owen-Smith, J. 2001. Managing laboratory work through skepticism: Processes of evaluation and control. *American Sociological Review*, 66(3): 427-452.
- Polanyi, M. 1966. *The Tacit Dimension*: University of Chicago Press.
- Postrel, S. 2002. Islands of shared knowledge: Specialization and mutual understanding in problem-solving teams. *Organization Science*, 13(3): 303-320.
- Puranam, P. 2012. A Future for the science of organization design. *Journal of Organization Design*, 1(1): 18-19.
- Puranam, P., Alexy, O., & Reitzig, M. 2014. What's “new” about new forms of organizing? *Academy of Management Review*, 39(2): 162-180.
- Rennie, D., Yank, V., & Emanuel, L. 1997. When authorship fails: A proposal to make contributors accountable. *Journal of the American Medical Association*, 278(7): 579-580.
- Shibayama, S., Baba, Y., & Walsh, J. P. 2015. Organizational design of university laboratories: Task allocation and lab performance in Japanese bioscience laboratories. *Research Policy*, 44(3): 610-622.
- Simon, H. A. 1962. The architecture of complexity. *Proceedings of the American Philosophical Society*: 467-482.
- Simonton, D. K. 2003. Scientific creativity as constrained stochastic behavior: the integration of product, person, and process perspectives. *Psychological Bulletin*, 129(4): 475-494.
- Singh, J., & Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? *Management Science*, 56(1): 41-56.
- Smith, A. 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations*.
- Stephan, P. 2012. *How Economics Shapes Science*: Harvard University Press.
- Stigler, G. J. 1951. The division of labor is limited by the extent of the market. *The Journal of Political Economy*: 185-193.
- Takeishi, A. 2002. Knowledge partitioning in the interfirm division of labor: The case of automotive product development. *Organization Science*, 13(3): 321-338.
- Teodoridis, F. 2013. Generalists, specialists, and the direction of inventive activity, *Working Paper*.
- Thompson, J. D. 1967. *Organizations in Action*.

- Van de Ven, A. H., Delbecq, A. L., & Koenig Jr, R. 1976. Determinants of coordination modes within organizations. *American Sociological Review*: 322-338.
- Von Hippel, E. 1990. Task partitioning: An innovation process variable. *Research Policy*, 19(5): 407-418.
- Walsh, J. P., & Lee, Y.-N. 2015. The bureaucratization of science. *Research Policy*, 44(8): 1584-1600.
- Wuchty, S., Jones, B., & Uzzi, B. 2007. The increasing dominance of teams in the production of knowledge. *Science*, 316(5827): 1036-1039.

Table 1: Descriptive statistics

	Mean	SD	Min	Max
Author level (n=83727)				
Main variables				
i_conceived	0.48		0	1
i_performed	0.51		0	1
i_analyzed	0.58		0	1
i_materials	0.34		0	1
i_wrote	0.47		0	1
i_other	0.09		0	1
i_countcontributions	2.48	1.25	1	6
i_sharecontributions	0.51	0.26	0.17	1
Controls				
i_priorpubsquantity	2.03	1.27	0	5.30
i_priorpubsquality	1.40	0.82	0	6.72
i_professionalage	12.56	10.73	0	60
i_institutionenrank	5.61	2.70	1	8
i_developing country	0.12		0	1
Activity and Team level (n=12995)				
Main variables				
a_countconceived	3.17	1.94	1	20
a_countperformed	3.46	2.40	1	20
a_countmaterials	3.18	2.40	1	20
a_countanalyzed	3.78	2.50	1	20
a_countwrote	3.04	1.97	1	20
a_countother	3.23	2.62	1	17
a_shareconceived	0.56	0.27	0.05	1
a_shareperformed	0.54	0.23	0.06	1
a_sharematerials	0.48	0.26	0.05	1
a_shareanalyzed	0.63	0.27	0.06	1
a_sharewrote	0.55	0.30	0.05	1
a_shareother	0.48	0.28	0.05	1
ti_avg_countcontributions	2.66	0.76	1	6
ti_avg_shareofcontributions	0.56	0.17	0.18	1
ti_shareofspecialists	0.16		0	0.94
ti_shareofmedspec	0.47		0	1
ti_shareofgeneralists	0.37		0	1
ta_avg_countauthors	3.31	1.61	1.00	16.80
ta_avg_shareauthors	0.56	0.17	0.18	1
t_teamsize	6.44	3.53	2	20
t_field_novel	0.21		0	1
t_numberfields_1	0.20		0	1
t_numberfields_2&3	0.65		0	1
t_numberfields_>3	0.16		0	1
t_citations	23.80	28.17	0	555
ti_avg_agg_pubsquality	4.55	4.62	0	259
Controls				
t_firm	0.14		0	1
t_funding_basic	0.31		0	1
t_funding_industry	0.05		0	1
t_funding_other	0.61		0	1
t_affiliations	3.31	2.06	1	22
t_country_US	0.38		0	1
t_country_developing	0.09		0	1
t_totalactivities	4.80	0.68	1	6
t_pages	9.96	3.29	2	51
t_publication_date	18126.01	364.82	17204	18878

Table 2: Interdependencies between activities

VARIABLES	1 i_wrote	2 i_analyzed	3 i_materials	4 i_performed	5 i_conceived	6 i_other
i_conceived	0.415** (0.004)	0.087** (0.005)	-0.041** (0.006)	0.015** (0.005)		-0.058** (0.011)
i_performed	-0.034** (0.004)	0.077** (0.005)	-0.192** (0.006)		0.013** (0.005)	-0.221** (0.010)
i_materials	-0.022** (0.004)	-0.085** (0.005)		-0.167** (0.005)	-0.040** (0.005)	-0.086** (0.012)
i_analyzed	0.244** (0.004)		-0.095** (0.006)	0.082** (0.005)	0.079** (0.004)	-0.080** (0.010)
i_wrote		0.306** (0.005)	-0.026** (0.006)	-0.042** (0.005)	0.474** (0.004)	-0.182** (0.012)
i_other	-0.163** (0.009)	-0.095** (0.010)	-0.126** (0.014)	-0.225** (0.010)	-0.051** (0.010)	
i_priorpubsquantity	0.010** (0.002)	-0.003 (0.002)	0.026** (0.003)	-0.107** (0.002)	0.044** (0.002)	0.013** (0.005)
i_priorpubsquality	0.009** (0.002)	0.021** (0.003)	0.016** (0.003)	0.026** (0.003)	0.011** (0.002)	-0.002 (0.006)
i_professionalage	0.002** (0.000)	-0.005** (0.000)	0.002** (0.000)	-0.011** (0.000)	0.003** (0.000)	0.002** (0.000)
i_institutionenrank	-0.008** (0.001)	-0.005** (0.001)	0.008** (0.001)	-0.003* (0.001)	-0.004** (0.001)	-0.000 (0.002)
i_developing country	-0.012 (0.009)	-0.093** (0.011)	0.052** (0.013)	0.081** (0.012)	0.025* (0.011)	0.056** (0.019)
Constant	0.162** (0.008)	0.483** (0.009)	0.499** (0.011)	0.898** (0.008)	0.103** (0.008)	0.637** (0.018)
Observations	83,727	83,050	63,594	80,278	82,672	16,609
R-squared	0.330	0.168	0.092	0.284	0.299	0.156
Number of papers	12,995	12,859	9,048	12,317	12,785	2,330

Note: OLS with paper fixed effects standard errors clustered at the level of the individual *=significant at 5%, **=significant at 1%.

Table 3: Division of labor and team size

VARIABLES	1 ti_avg_share ofcontributions	2 ti_share ofspecialists	3 ti_share ofmedspec	4 ti_share ofgeneralists	5 a_share conceived	6 a_share performed	7 a_share materials	8 a_share analyzed	9 a_share wrote	10 a_share other
t_teamsize	-0.068** (0.001)	0.046** (0.002)	0.062** (0.003)	-0.109** (0.002)	-0.097** (0.002)	-0.012** (0.002)	-0.062** (0.003)	-0.058** (0.002)	-0.108** (0.002)	-0.038** (0.006)
t_teamsize_sq	0.003** (0.000)	-0.001** (0.000)	-0.003** (0.000)	0.004** (0.000)	0.004** (0.000)	0.001** (0.000)	0.002** (0.000)	0.002** (0.000)	0.004** (0.000)	0.001** (0.000)
t_totalactivitieslisted	-0.057** (0.002)	0.094** (0.003)	0.001 (0.004)	-0.095** (0.003)	-0.034** (0.003)	-0.060** (0.003)	-0.038** (0.006)	-0.041** (0.004)	-0.047** (0.003)	-0.090** (0.007)
t_pages	0.002** (0.000)	-0.001 (0.001)	-0.003** (0.001)	0.003** (0.001)	-0.001 (0.001)	0.005** (0.001)	0.000 (0.001)	0.006** (0.001)	-0.002** (0.001)	0.001 (0.002)
t_publication_date	0.000** (0.000)	-0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000** (0.000)	-0.000 (0.000)
t_firm	-0.000 (0.003)	-0.007 (0.005)	0.013 (0.007)	-0.006 (0.006)	-0.004 (0.006)	-0.002 (0.006)	0.006 (0.008)	0.017* (0.007)	-0.013* (0.006)	-0.008 (0.015)
t_funding_basic	0.008 (0.006)	-0.011 (0.009)	0.003 (0.011)	0.009 (0.010)	0.015 (0.010)	0.011 (0.010)	0.005 (0.013)	0.005 (0.011)	-0.005 (0.010)	0.030 (0.024)
t_funding_industry	0.008 (0.006)	-0.008 (0.010)	-0.005 (0.013)	0.013 (0.011)	0.006 (0.012)	0.021 (0.011)	-0.015 (0.015)	-0.001 (0.013)	0.009 (0.012)	0.048 (0.027)
t_funding_other	0.000 (0.006)	-0.003 (0.008)	0.000 (0.011)	0.002 (0.010)	-0.001 (0.010)	0.010 (0.010)	0.002 (0.013)	-0.002 (0.011)	-0.014 (0.010)	0.038 (0.024)
t_affiliations	0.004** (0.001)	-0.003** (0.001)	-0.001 (0.001)	0.004** (0.001)	0.008** (0.001)	-0.019** (0.001)	0.013** (0.002)	-0.003 (0.001)	0.015** (0.001)	0.016** (0.003)
t_country_first_US	0.001 (0.003)	0.005 (0.004)	-0.008 (0.005)	0.003 (0.005)	-0.021** (0.005)	0.020** (0.005)	-0.000 (0.006)	0.015** (0.005)	-0.006 (0.005)	-0.030* (0.013)
t_country_first_developing	-0.013** (0.004)	0.025** (0.006)	-0.012 (0.008)	-0.012 (0.007)	-0.034** (0.007)	0.005 (0.007)	-0.004 (0.009)	-0.000 (0.008)	-0.020** (0.008)	-0.031 (0.019)
Field fixed effects	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.877** (0.058)	-0.201* (0.088)	0.101 (0.115)	1.100** (0.102)	0.731** (0.105)	0.831** (0.099)	0.789** (0.140)	0.751** (0.115)	0.814** (0.108)	1.487** (0.255)
Observations	12,995	12,995	12,995	12,995	12,785	12,317	9,048	12,859	12,995	2,330
R-squared	0.432	0.266	0.080	0.376	0.285	0.106	0.112	0.144	0.360	0.208

Note: OLS. *=significant at 5%, **=significant at 1%

Table 4: Differences in division of labor across types of projects

VARIABLES	1 ti_avg_share ofcontributions	2 ti_share ofspecialists	3 ti_share ofmedspec	4 ti_share ofgeneralists	5 a_share conceived	6 a_share performed	7 a_share materials	8 a_share analyzed	9 a_share wrote	10 a_share other
t_field_novel	-0.011** (0.003)	0.009* (0.004)	0.009 (0.006)	-0.018** (0.005)	-0.009 (0.005)	-0.051** (0.005)	0.009 (0.007)	-0.010 (0.006)	0.014* (0.005)	-0.023 (0.014)
t_numberfields_1	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
t_numberfields_2&3	0.008** (0.003)	-0.013** (0.005)	0.003 (0.006)	0.010* (0.005)	0.002 (0.005)	0.013** (0.005)	-0.005 (0.007)	0.037** (0.006)	-0.006 (0.006)	-0.006 (0.015)
t_numberfields_>3	0.019** (0.004)	-0.023** (0.006)	-0.006 (0.008)	0.029** (0.007)	0.012 (0.007)	0.031** (0.007)	0.003 (0.009)	0.057** (0.008)	-0.003 (0.007)	-0.010 (0.019)
t_totalactivities	-0.057** (0.002)	0.096** (0.003)	-0.003 (0.003)	-0.093** (0.003)	-0.033** (0.003)	-0.061** (0.003)	-0.036** (0.006)	-0.038** (0.004)	-0.049** (0.003)	-0.099** (0.006)
t_pages	0.001** (0.000)	0.001 (0.001)	-0.003** (0.001)	0.002** (0.001)	-0.002** (0.001)	0.006** (0.001)	-0.001 (0.001)	0.007** (0.001)	-0.005** (0.001)	-0.001 (0.001)
t_publication_date	0.000** (0.000)	-0.000** (0.000)	0.000 (0.000)	0.000* (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000** (0.000)	-0.000 (0.000)
t_firm	-0.001 (0.003)	-0.005 (0.005)	0.012 (0.007)	-0.008 (0.006)	-0.006 (0.006)	-0.001 (0.006)	0.005 (0.007)	0.016* (0.007)	-0.016* (0.006)	-0.016 (0.015)
t_funding_basic	0.003 (0.006)	0.000 (0.009)	-0.005 (0.011)	0.004 (0.010)	0.011 (0.010)	0.018 (0.010)	-0.009 (0.013)	0.016 (0.011)	-0.024* (0.010)	0.017 (0.024)
t_funding_industry	0.006 (0.006)	-0.008 (0.010)	-0.002 (0.013)	0.010 (0.011)	0.005 (0.012)	0.021 (0.011)	-0.022 (0.015)	0.002 (0.013)	0.003 (0.012)	0.054* (0.027)
t_funding_other	-0.003 (0.005)	0.006 (0.008)	-0.005 (0.011)	-0.001 (0.010)	-0.005 (0.010)	0.017 (0.010)	-0.010 (0.013)	0.005 (0.011)	-0.028** (0.010)	0.032 (0.024)
t_affiliations	0.005** (0.001)	-0.006** (0.001)	-0.000 (0.001)	0.006** (0.001)	0.010** (0.001)	-0.021** (0.001)	0.017** (0.002)	-0.007** (0.001)	0.021** (0.001)	0.021** (0.003)
t_country_first_US	-0.000 (0.003)	0.004 (0.004)	-0.007 (0.005)	0.002 (0.005)	-0.022** (0.005)	0.017** (0.005)	-0.001 (0.006)	0.016** (0.005)	-0.008 (0.005)	-0.029* (0.013)
t_country_first_developing	-0.007 (0.004)	0.015* (0.006)	-0.010 (0.008)	-0.005 (0.007)	-0.026** (0.007)	0.000 (0.007)	0.000 (0.009)	0.000 (0.008)	-0.005 (0.008)	-0.019 (0.018)
Team size dummies	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.734** (0.057)	-0.063 (0.088)	0.181 (0.113)	0.882** (0.100)	0.564** (0.104)	0.774** (0.099)	0.698** (0.138)	0.603** (0.115)	0.622** (0.108)	1.372** (0.255)
Observations	12,970	12,970	12,970	12,970	12,760	12,293	9,035	12,834	12,970	2,326
R-squared	0.440	0.254	0.101	0.389	0.290	0.087	0.110	0.120	0.349	0.186

Note: OLS. *=significant at 5%, **=significant at 1%

Table 5: Differences in interdependencies between activities across types of projects

VARIABLES	1	2	3	4	5	6	7	8	9	10	11	12
	i_wrote	i_analyzed	i_materials	i_performed	i_conceived	i_other	i_wrote	i_analyzed	i_materials	i_performed	i_conceived	i_other
int_novel_conceived	-0.012 (0.010)	0.001 (0.012)	-0.033* (0.015)	-0.008 (0.012)		-0.094** (0.028)						
int_novel_performed	0.002 (0.009)	0.015 (0.011)	0.057** (0.013)		-0.012 (0.010)	-0.029 (0.022)						
int_novel_materials	0.001 (0.011)	0.004 (0.012)		0.030* (0.013)	-0.016 (0.012)	-0.026 (0.028)						
int_novel_analyzed	0.013 (0.010)		0.006 (0.015)	0.016 (0.012)	0.004 (0.011)	0.016 (0.024)						
int_novel_wrote		0.001 (0.012)	-0.006 (0.016)	0.001 (0.012)	-0.021* (0.011)	0.108** (0.031)						
int_novel_other	0.082** (0.023)	0.013 (0.024)	-0.039 (0.035)	-0.016 (0.023)	-0.105** (0.024)							
int_numberfields_conceived							0.006 (0.007)	0.015 (0.008)	-0.006 (0.010)	-0.000 (0.009)		-0.012 (0.020)
int_numberfields_performed							0.004 (0.006)	-0.020** (0.008)	-0.015 (0.009)		-0.006 (0.007)	-0.030 (0.017)
int_numberfields_materials							0.024** (0.007)	-0.007 (0.009)		-0.005 (0.008)	-0.007 (0.008)	0.012 (0.020)
int_numberfields_analyzed							0.002 (0.007)		-0.010 (0.010)	-0.012 (0.008)	0.012 (0.008)	0.033 (0.017)
int_numberfields_wrote								-0.010 (0.008)	0.037** (0.011)	-0.004 (0.008)	0.005 (0.007)	0.056* (0.022)
int_numberfields_other							0.046** (0.015)	0.028 (0.016)	0.018 (0.024)	-0.017 (0.018)	-0.009 (0.017)	
i_conceived	0.418** (0.005)	0.087** (0.005)	-0.034** (0.007)	0.016** (0.006)		-0.039** (0.012)	0.404** (0.015)	0.057** (0.018)	-0.029 (0.022)	0.015 (0.018)		-0.034 (0.041)
i_performed	-0.035** (0.004)	0.074** (0.005)	-0.204** (0.006)		0.016** (0.005)	-0.214** (0.011)	-0.042** (0.013)	0.118** (0.016)	-0.162** (0.019)		0.025 (0.015)	-0.158** (0.036)
i_materials	-0.023** (0.005)	-0.086** (0.006)		-0.174** (0.006)	-0.037** (0.005)	-0.080** (0.013)	-0.070** (0.015)	-0.070** (0.018)		-0.157** (0.018)	-0.025 (0.017)	-0.110* (0.044)
i_analyzed	0.242** (0.004)		-0.096** (0.006)	0.079** (0.006)	0.078** (0.005)	-0.081** (0.011)	0.240** (0.014)		-0.075** (0.021)	0.106** (0.018)	0.054** (0.016)	-0.147** (0.036)
i_wrote		0.306** (0.005)	-0.025** (0.007)	-0.042** (0.006)	0.478** (0.005)	-0.206** (0.013)		0.326** (0.018)	-0.101** (0.023)	-0.034 (0.018)	0.463** (0.015)	-0.294** (0.046)
i_other	-0.182** (0.010)	-0.097** (0.011)	-0.117** (0.015)	-0.222** (0.011)	-0.028** (0.010)		-0.256** (0.031)	-0.153** (0.033)	-0.164** (0.051)	-0.191** (0.037)	-0.032 (0.035)	
Control variables	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.162** (0.008)	0.484** (0.009)	0.499** (0.011)	0.898** (0.008)	0.102** (0.008)	0.635** (0.018)	0.162** (0.008)	0.483** (0.009)	0.499** (0.011)	0.898** (0.008)	0.102** (0.008)	0.637** (0.018)
Observations	83,557	82,880	63,507	80,115	82,502	16,578	83,727	83,050	63,594	80,278	82,672	16,609
R-squared	0.330	0.168	0.093	0.284	0.300	0.158	0.330	0.168	0.093	0.284	0.299	0.158
Number of papers	12,970	12,834	9,035	12,293	12,760	2,326	12,995	12,859	9,048	12,317	12,785	2,330

Note: OLS with article fixed effects. Control variables: i_Inpriorpubsquantity, i_Inpriorpubs_quality, i_professionalage, i_institutionrank, i_developing_country. *=significant at 5%, **=significant at 1%

Table 6: Division of labor and quality of the article

VARIABLES	1	2	3	4	5	6	7	8
	t_ln_citations	t_ln_citations	t_ln_citations	t_ln_citations	t_ln_citations	t_ln_citations	t_ln_citations	t_ln_citations
ti_avg_sharecontributions	-0.271** (0.049)	0.150** (0.056)			-0.315** (0.049)	0.184** (0.056)		
Team size dummies		incl.	incl.	incl.			incl.	incl.
ti_shareofspecialists	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
ti_shareofmedspecialization			-0.011 (0.037)				0.024 (0.038)	
ti_shareofgeneralists			0.080 (0.042)				0.114** (0.042)	
a_shareconceived				0.030 (0.032)				0.034 (0.033)
a_shareperformed				-0.004 (0.035)				0.020 (0.035)
a_sharematerials				-0.030 (0.029)				-0.027 (0.029)
a_shareanalyzed				-0.013 (0.029)				-0.029 (0.029)
a_sharewrote				0.150** (0.033)				0.181** (0.033)
a_shareother				-0.041 (0.041)				-0.021 (0.040)
Detailed field dummies	incl.	incl.	incl.	incl.				
t_field_novel					-0.085** (0.020)	-0.071** (0.019)	-0.071** (0.019)	-0.074** (0.019)
t_numberfields_1					omitted	omitted	omitted	omitted
t_numberfields_2&3					0.036 (0.020)	0.013 (0.019)	0.013 (0.019)	0.016 (0.019)
t_numberfields_>3					0.100** (0.026)	0.064* (0.025)	0.064* (0.025)	0.069** (0.025)
ti_avg_agg_pubquality	0.034** (0.008)	0.033** (0.008)	0.033** (0.008)	0.033** (0.007)	0.033** (0.007)	0.032** (0.007)	0.032** (0.007)	0.032** (0.007)
t_totalactivities	0.002 (0.012)	-0.000 (0.012)	-0.001 (0.012)	0.009 (0.015)	0.010 (0.012)	0.004 (0.012)	0.004 (0.012)	0.009 (0.015)
t_pagecount	0.035** (0.002)	0.031** (0.002)	0.031** (0.002)	0.032** (0.002)	0.031** (0.002)	0.027** (0.002)	0.027** (0.002)	0.028** (0.002)
t_firm	0.043* (0.022)	0.023 (0.022)	0.024 (0.022)	0.026 (0.022)	0.044* (0.022)	0.021 (0.022)	0.021 (0.022)	0.024 (0.022)
t_funding_basic_orga	0.110** (0.039)	0.099* (0.039)	0.099* (0.039)	0.101** (0.039)	0.103** (0.040)	0.085* (0.039)	0.086* (0.039)	0.089* (0.039)
t_funding_ind01	0.079 (0.046)	0.042 (0.045)	0.042 (0.045)	0.042 (0.045)	0.100* (0.046)	0.047 (0.045)	0.047 (0.045)	0.047 (0.045)
t_funding_other	0.078* (0.038)	0.070 (0.037)	0.070 (0.037)	0.072 (0.037)	0.089* (0.038)	0.075* (0.038)	0.075* (0.038)	0.078* (0.038)
t_no_affiliations	0.041** (0.004)	-0.003 (0.005)	-0.003 (0.005)	-0.004 (0.005)	0.047** (0.004)	-0.001 (0.005)	-0.001 (0.005)	-0.003 (0.005)
t_country_first_US	0.015 (0.019)	0.037* (0.019)	0.037 (0.019)	0.039* (0.019)	0.027 (0.019)	0.047* (0.019)	0.046* (0.019)	0.049* (0.019)
t_country_first_developing	-0.065* (0.027)	-0.085** (0.027)	-0.086** (0.027)	-0.084** (0.026)	-0.059* (0.027)	-0.084** (0.026)	-0.085** (0.026)	-0.084** (0.026)
Publishing month/year dummies	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	2.467** (0.150)	2.140** (0.149)	2.204** (0.148)	2.080** (0.147)	2.498** (0.149)	2.167** (0.147)	2.219** (0.146)	2.108** (0.144)
Observations	12,995	12,995	12,995	12,995	12,970	12,970	12,970	12,970
R-squared	0.193	0.211	0.211	0.212	0.168	0.190	0.190	0.192

Note: OLS. *=significant at 5%, **=significant at 1%

APPENDIX

1 More detailed information on levels of contributions

Our basic framework required information only on whether or not a contributor participated in a particular activity. We can extend the discussion to three cases when more information is available: (1) information on the shares of individuals' total effort devoted to different activities (e.g., team members declare what share of their total time they spent on each activity) (2) information on the share of effort contributed to a given activity by different individuals (e.g., teams declare what share of an activity was performed by each team member), and (3) information on the units of effort contributed by different individuals to different activities (e.g., hours or days). While our data do not include this level of detail, more detailed data may become available in the future and it is useful to briefly explore these cases to provide a more general framework.

1.1 Information about shares of individuals' total effort devoted to particular activities

Figure A1 illustrates the case when shares of effort are known at the level of the individual. Compared to the base case, this scenario provides more detailed information on how individuals allocate their effort across activities. For example, individual 1 spent 50% of her time on activity 1, 20% on activity 2 and 30% on activity 4. In addition to the indicators of specialization discussed above (count of activities and share of all activities performed), this additional information allows us to compute a more nuanced measure. One possibility is to draw on the commonly used Herfindahl index. More specifically, we can compute $S_i = \sum_{j=1}^K \alpha_{ij}^2$, where α_{ij} is now the share of time devoted by member i to activity j . The larger the share of an individual's time that is devoted to a small number of activities, the higher is S_i . In the extreme case, $S_i=1$ if the team member spends all her time on a single activity (maximum specialization). If an individual's effort is evenly distributed across all K activities then $S_i=1/K$ (the team member is an extreme generalist). The average of the individual measures, $S_i = \frac{\sum_{i=1}^N S_i}{N}$, provides a team-level measure of the degree to which members work as specialists versus generalists.

Figure A1: Information about shares of individuals' total effort devoted to particular activities

		Activity				Herfindahl-based
		1	2	3	4	S_i
Team member	1	0.50	0.20		0.30	0.38
	2	0.33	0.33		0.33	0.33
	3			1.00		1.00
	4	0.60	0.40			0.52
	5	0.25	0.25	0.25	0.25	0.25
Avg. (S_i): 0.50						

1.2 Information about the shares of activities' total volume performed by each member

In a second case, information is available about effort allocation at the level of the activity. For example, *Science* magazine has recently begun to ask authors to indicate what share of a given contribution was performed by each author.¹ Fig. A2 shows an example where 30% of activity 1 were performed by team member 1, 20% by team member 2, 35% by team member 4 and 15% by team member 5. In addition to the earlier measures (the number of team members and the share of team members involved in an activity), we can now compute a more nuanced activity level measure. One possibility is the Herfindahl-based measure $C_j = \sum_{i=1}^N \beta_{ij}^2$, where β_{ij} is the share of activity j performed by team member i . The larger C_j , the more highly concentrated an activity is among a small number of team members. In the extreme case, $C_j=1$ if only one team member performs the activity. If the activity is evenly distributed among all N team members, then $C_j=1/N$. The average of the activity level measures, $C_t = \frac{\sum_{j=1}^K C_j}{K}$, provides a team-level measure of the degree to which activities are concentrated versus distributed across team members.

Figure A2: Information about the shares of activities' total volume performed by each member

		Activity				
		1	2	3	4	
Team member	1	0.30	0.15		0.40	
	2	0.20	0.30		0.40	
	3			0.80		
	4	0.35	0.30			
	5	0.15	0.25	0.20	0.20	
Sum		1.00	1.00	1.00	1.00	
Herfindahl-based C_j		0.28	0.27	0.68	0.36	Avg. (C_t): 0.40

1.3 Effort from different individuals towards different activities

Finally, information may be available on the absolute level of effort spent by each team member on each activity (e.g., in hours, or days). This information allows us to compute the shares of individuals' total effort devoted to particular activities (individual level; scenario 1 above) as well as the share of the volume of a particular activity performed by different team members (activity level; scenario 2 above) and we can again compute the respective Herfindahl-based measures.

A novel aspect of this scenario is that we can compute an individual's share of the total team effort, w_i , and an activity's share of the total volume of work, w_j . Consider the example shown in Fig. A3. Individual 1 contributed 15 units of effort, which represented 26% of the total effort spent on the project. Similarly, activity 1 received 26 units of effort, which represented 45% of the total volume of work. We

¹ <https://www.sciencemag.org/site/feature/contribinfo/prep/coi.pdf>, accessed January 3, 2016.

can then use these shares as weights when computing the team-level averages. More specifically, $S_{tw} = \frac{\sum_{i=1}^N w_i S_i}{N}$ is a team-level measure of members' degree of specialization, giving more weight to members who contributed more effort to the project. Similarly, $C_{tw} = \frac{\sum_{j=1}^K w_j C_j}{K}$ is a team-level measure of the activities' degree of concentration, giving more weight to activities that required a larger amount of work.

Figure A3: Levels of effort contributed by each team member to each activity

Raw data (units of effort)							Shares of individual effort						
	Activity					Sum of indiv. effort	Share of team effort (w_i)	Activity				Herfindahl-based	
	1	2	3	4	5			1	2	3	4	Sum	S_i
Team member	1	10	2		3	15.00	0.26	0.67	0.13		0.20	1.00	0.50
	2	3	2		5	10.00	0.17	0.30	0.20		0.50	1.00	0.38
	3				3	3.00	0.05			1.00		1.00	1.00
	4	10	4			14.00	0.24	0.71	0.29			1.00	0.59
	5	3	3	7	3	16.00	0.28	0.19	0.19	0.44	0.19	1.00	0.30
Volume of activity		26.00	11.00	10.00	11.00	Total effort/work: 58							
Share of total work (w_i)		0.45	0.19	0.17	0.19								
Shares of activity volume													
Team member	1	0.38	0.18		0.27								
	2	0.12	0.18		0.45								
	3				0.30								
	4	0.38	0.36										
	5	0.12	0.27	0.70	0.27								
Sum		1.00	1.00	1.00	1.00								
Herfindahl-based C_j		0.32	0.27	0.58	0.36								
unweighted average (C_j): 0.38													
weighted average (C_{tw}): 0.36													
unweighted average (S_i): 0.55													
weighted average (S_{tw}): 0.47													