NBER WORKING PAPER SERIES

THE DIVISION OF LABOR IN TEAMS:
A CONCEPTUAL FRAMEWORK AND APPLICATION TO COLLABORATIONS IN SCIENCE

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Working Paper 22241
http://www.nber.org/papers/w22241

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2016

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NBER Working Paper No. 22241
May 2016
JEL No. J24,O31,O32

ABSTRACT

Even though teams have become the dominant mode of knowledge production, little is known regarding how they divide work among their members. Conceptualizing knowledge production as a process involving a number of functional activities, we first develop a conceptual 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 vs. work as generalists), (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 (e.g., which activities are performed jointly by the same individual). We then employ this framework to explore team-based knowledge production using a newly available type of data – the 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 how division of labor is related to the quality of teams' research output. We discuss opportunities for extending and applying our framework as well as implications for scientists and policy makers.

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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 (Gruber et al., 2013; Simonton, 2003), 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 (Bercovitz & Feldman, 2011; Jones, 2009; Singh & Fleming, 2010; Teodoridis, 2013). A complementary view emphasizes that the research process involves a number of different functional activities, ranging from the generation of research hypotheses and the design of experiments to the codification of research results in a scientific paper (Hagstrom, 1964; Knorr-Cetina, 1999; Latour & Woolgar, 1979; Owen-Smith, 2001). In this view, collaboration in teams can provide efficiency gains from functional specialization and the sharing of resources. In a similar vein, observers have likened contemporary research labs to "firms" that rely on the efficient division of labor among specialized individuals (Freeman et al., 2001; Hackett, 1990; Stephan, 2012). Despite rich qualitative studies, however, we have a limited understanding of the division of labor in teams. For one, prior work has discussed the organization of teams from different angles, yet we lack a common 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 how team members divide and allocate work in collaborative knowledge production (Shibayama et al., 2015; Stephan, 2012).

Adopting a process-based view of knowledge production, 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 concentrated among few team members vs. distributed across many. 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 individual. While prior research 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 apply 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, 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. 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 higher division of labor than those working in established fields, and the 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. Finally, we examine how different aspects of division of labor in a team relate to the quality and impact of the resulting paper, as measured by citations.

Our work contributes to a number of literatures. First, we contribute to a growing literature on the production of knowledge and the economics of science (Dasgupta & David, 1994; Jones & Weinberg, 2011; Singh & Fleming, 2010; Stephan, 2012; Wuchty et al., 2007). Complementing the common focus on collaborators as contributors of different pieces of knowledge, we examine 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 on its role in shaping innovative performance.

We also contribute to the more general 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 (Hamilton et al., 2003; Smith, 1776). We consider how some of the fundamental concepts from that literature translate into the increasingly

[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 possess the required knowledge.

important context of team-based knowledge production and introduce a novel data source that should prove useful for future research.

Our conceptual framework and empirical results may also be useful for scientists, research administrators, and 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; Fuhrmann et al., 2011; National Academies, 2014). 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 (Franzoni & Sauermann, 2014; Nielsen, 2011).

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., Arora et al., 2016; Becker & Murphy, 1992; Gibbs & Poston, 1975; Hagstrom, 1964; Puranam et al., 2014; Smith, 1776). We draw on these discussions to develop a conceptual framework that allows us to characterize 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…K) distinct activities or tasks. These activities can be distributed among a number of (i=1…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 in Figure 1. For each team, the columns refer to a set of functional activities that need to be performed to produce the 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 activity vs. perform a range of activities (within individual, across activities), the degree to which activities are performed by one person vs. multiple persons (within activity, 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.

[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.

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 $G_i = \frac{\sum_{j=1}^{K} \alpha_{ij}}{K}$, which describes the degree to which individual i performs a large share of the activities ("*generalist*") or performs only a small share of 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 5 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 activities 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 a large share of 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 a minimum 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 less concentrated. 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

		Activity				Count of	Share of
		1	2	3	4	activities	activities (G_i)
Member	1	1	0	0	0	1	25%
	2	0	1	0	0	1	25%
	3	0	0	0	1	1	25%
	4	0	0	0	1	1	25%
	5	0	1	1	0	2	50%
							Avg. (G_t): 30%
Count of members		1	2	1	2		
Share of members (D_j)		20%	40%	20%	40%	Avg. (D_t): 30%	

Correlations (ρ_{jl})	Act. 1	Act.2	Act.3	Act.4
Act.1		-0.41	-0.25	-0.41
Act.2			0.61	-0.67
Act.3				-0.41
Avg. ρ_{jl} (I_j)	-0.36	-0.15	-0.02	-0.49
Avg. I_j (I_t)				**-0.25**

TEAM B

		Activity				Count of	Share of
		1	2	3	4	activities	activities (G_i)
Member	1	1	1	0	1	3	75%
	2	1	1	0	1	3	75%
	3	0	0	1	0	1	25%
	4	1	1	0	1	3	75%
	5	1	1	1	1	4	100%
							Avg. (G_t): 70%
Count of members		4	4	2	4		
Share of members (D_j)		80%	80%	40%	80%	Avg. (D_t): 70%	

Correlations (ρ_{jl})	Act. 1	Act.2	Act.3	Act.4
Act.1		1.00	-0.61	1.00
Act.2			-0.61	1.00
Act.3				-0.61
Avg. ρ_{jl} (I_j)	0.46	0.46	-0.61	0.46
Avg. I_j (I_t)				**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, all individuals who perform activity 1 also perform activity 2, resulting in a positive correlation between these two activities. In contrast, individuals who perform activity 1 tend not to be involved in activity 3, resulting in a negative correlation. Denoting the correlation between activity j and another activity l (l=1…K, with l≠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 with others could be called *interdependent*, while those that tend to have negative relationships with other activities are more *independent*. Averaging all correlations between activities results in the team level measure $I_t=\frac{\sum_{j=1}^{K}I_j}{K}$.[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 Pearson product-moment correlation coefficients, one could use other measures of association.

2.2 Potential efficiency gains from division of labor

The conceptual framework allows us to describe division of labor in teams using three perspectives. We now briefly discuss mechanisms that have been proposed to explain each of the three aspects of division of labor. In doing so, we focus on arguments made by economists and organizational theorists, who emphasize potential efficiency gains from division of labor (Becker & Murphy, 1992; Hagstrom, 1964; Smith, 1776). The objective of our discussion is not to derive testable hypotheses but to connect the framework more explicitly to relevant 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 and repeatedly engaging in a particular activity can allow individuals to learn how to perform this activity more efficiently ("learning by doing"). Moreover, learning may become increasingly easy as an individual's stock of knowledge about an activity 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 (i.e., a lower score on the measure G_i from Section 2.1) and more division of labor.

Second, if an activity requires worker-specific investments such as tools, instruments, or 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 of activities (i.e., a lower score on D_j) and more division of labor.

Potential benefits from specialization and concentration, however, may be offset by higher costs of coordination. One driver of these costs are interdependencies between activities (Becker & Murphy, 1992; Cummings & Kiesler, 2014; Puranam et al., 2014; Simon, 1962). As highlighted by organizational scholars, 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 intermediate 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 if different workers perform 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 (Osterloh & Frey, 2000; Polanyi, 1966). 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 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, implying a positive correlation between the two activities (ρ_{jl} in our framework).

Teams may also 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 interdependencies 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. Conversely, if the results of sub-activities can easily be pooled to get the desired output, multiple individuals can work independently and in parallel, allowing a higher degree of distribution of this activity. This discussion higlights an important point: While one can study how teams divide work within a given activity (e.g., by considering more detailed sub-activities), we conceptualize division of labor with respect to a given set of activities at a pre-defined level of aggregation (the columns in Figure 1). Focusing on activities at a fixed level of aggregation ensures that activities are meaningful and distinct, and can be compared across teams. This approach is also consistent with current efforts to develop standard classifications of work activities and to document team members' contributions using comparable categories (Allen et al., 2014). Indeed, such efforts provide the data for the following part of the paper, which applies our conceptual framework to gain empirical insights into 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, with a 2014 Impact Factor of 3.23. *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 suitable for two reasons. First, they allow us to gain insights into a broad range of scientific projects since articles span a range of fields (primarily in the domains of biology, life sciences, and medicine) and vary considerably in quality and impact. The latter aspect is particularly useful because it mitigates concerns about selection bias; whereas publications in highly selective journals such as *Science* or *Nature* reflect work in 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. The second important feature is that *PLOS ONE* is a pioneer in requiring authors to disclose the contributions made by each team member, which allows us to gain unique insights into team members' activities (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 classification of contributions 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)

[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 ONE* publication for the very common name *Ying LIU* and 783 publications for *Lin XU*. We also dropped a small number of papers with individuals for whom Scopus returned publications that were more than 60 years old.

since the organization of knowledge production may be qualitatively different in big science projects (see Bikard et al., 2015) and since 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 (a_{ij} in our framework). For non-standard contributions, a free-text field "other" allows authors to indicate additional contributions and which individuals performed 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 project participants. In particular, our measure does not capture work done by any "ghost authors", individuals who made significant contributions but are not listed as authors (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 importantly, they allow us to examine division of labor in a large sample of projects, complementing prior qualitative work

[7] The "other" contributions included items such as "developed design of simulation", "critically revised the method", "performed subject recruitment", or "found the grant".

using small numbers of cases (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 (Ivaniš et al., 2011; Kamo, 2000). The contributions listed on published 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 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*; G_i in our framework). 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 <=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* (G_t in our framework). 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_shareofmedspecialization*.

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

[8] *PLOS ONE* encourages authors 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 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.

a_shareother (D_j in our framework). We average these measures across activities to obtain two team level measures, *ta_avgcountauthors* and *ta_avgshareauthors* (D_t in our framework).

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

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

--- Table 1 about here ---

4 Characterizing division of labor in teams

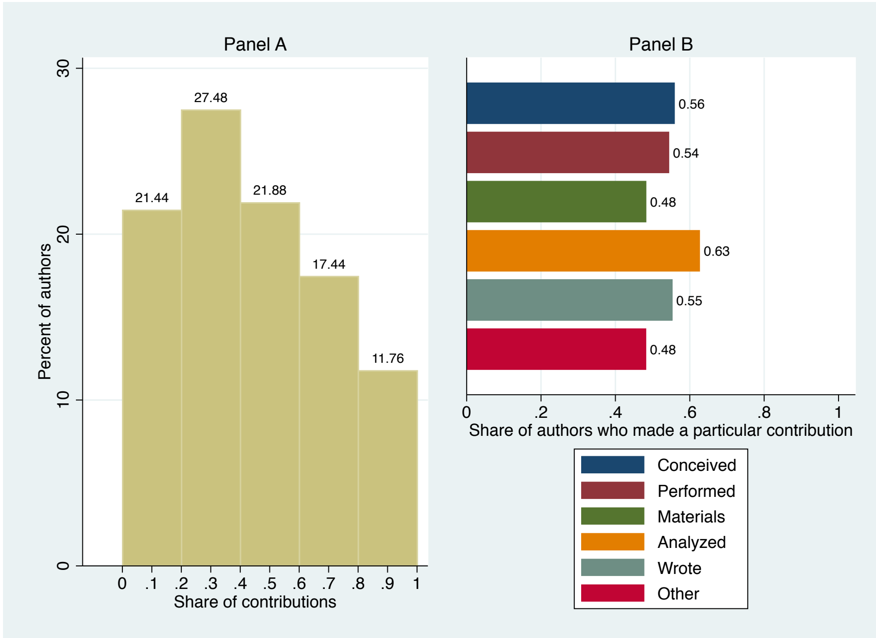
4.1 Individual level and activity level perspectives

The average team has 6.44 members; 87.04% of teams have 10 or fewer members and 97.67% 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 is somewhat lower (70%), suggesting that many but not all projects require this type of input (see Furman & Stern, 2011). Only 18% of articles 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 2.48 different activities. Using the relative measure (*i_sharecontributions*), 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 3.31 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 team members: The average 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_sharecontributions*). Panel B shows the average share of team members performing a particular activity (e.g., *a_shareconceived*), conditional upon that activity being listed on the paper.

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*<=0.2, Figure 3, panel A), have medium specialization (*i_sharecontributions*>0.2 but <=0.6, panel B), and are generalists (*i_sharecontributions*>0.6, panel C). Figure 3 shows that *performed* and *materials* (as well as *other*) have the highest shares 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 (e.g., *i_wrote*) on the 5 remaining activities. Since we are interested in how activities are correlated within a given team, we estimate these regressions using linear probability models (LPM) with article fixed effects.

The article fixed effects control for unobserved heterogeneity across projects. In addition, we include a number of individual level controls. First, we code a number of variables based on author affiliations. We measure the reputation of an author's institution using the 2012 Academic Ranking of World Top 500 Universities (the so-called Shanghai ranking). The variable *i_institutionrank* 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. For authors with more than one affiliation, we used the highest-ranked institution. 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 ONE* articles, we obtained data on authors' prior publications using the Scopus database. We use the log of the number of publications over the five years prior to the focal *PLOS ONE* article as a measure of the quantity of prior publications (*i_lnpriorpubs_quantity*). We use the log of 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_lnpriorpubs_quality*). We estimate *i_professionalage* as the difference between the year of the *PLOS ONE* paper and the year of the author's 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 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.

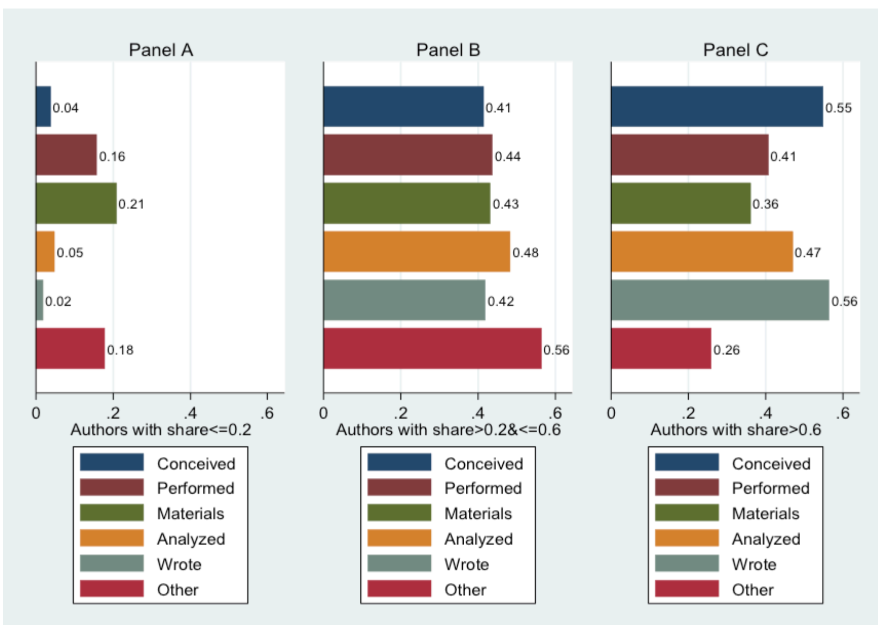
Model 1 in Table 2 uses as dependent variable the dummy indicating whether a team member has contributed by writing the paper (*i_wrote*). We find a strong positive relationship with *conceived* and *analyzed*, consistent with the notion that writing involves the integration of conceptual ideas and empirical 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). 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, suggesting that individuals who perform experiments are unlikely to also provide materials. 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. Models 5 and 6 examine the predictors of a team member having conceived the study or performed an "other" activity and are consistent with the earlier results.

Although the focus of Table 2 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 is a relatively independent activity.[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 is a factor analysis of the activity measures. Using this approach, one factor with eigenvalue >1 emerges, with the largest loadings for *i_conceived, i_wrote,* and *i_analyzed*. Two 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

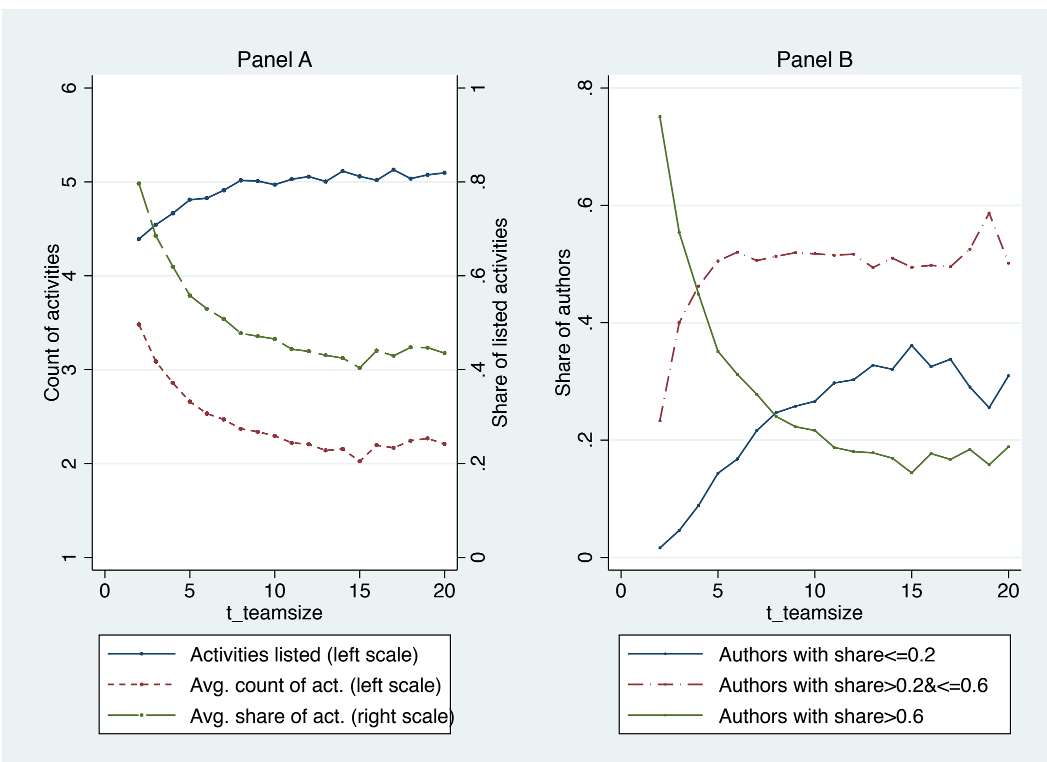
Prior literature suggests that division of labor may depend on the total volume of work and the size of the organization (Becker & Murphy, 1992; Jones, 2009; Smith, 1776; Stigler, 1951). As such, we now use our framework to explore how the division of labor differs across teams of different size.

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 (*t_totalactivitieslisted*), which increases from roughly 4.5 for small teams to roughly 5 for larger teams.

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



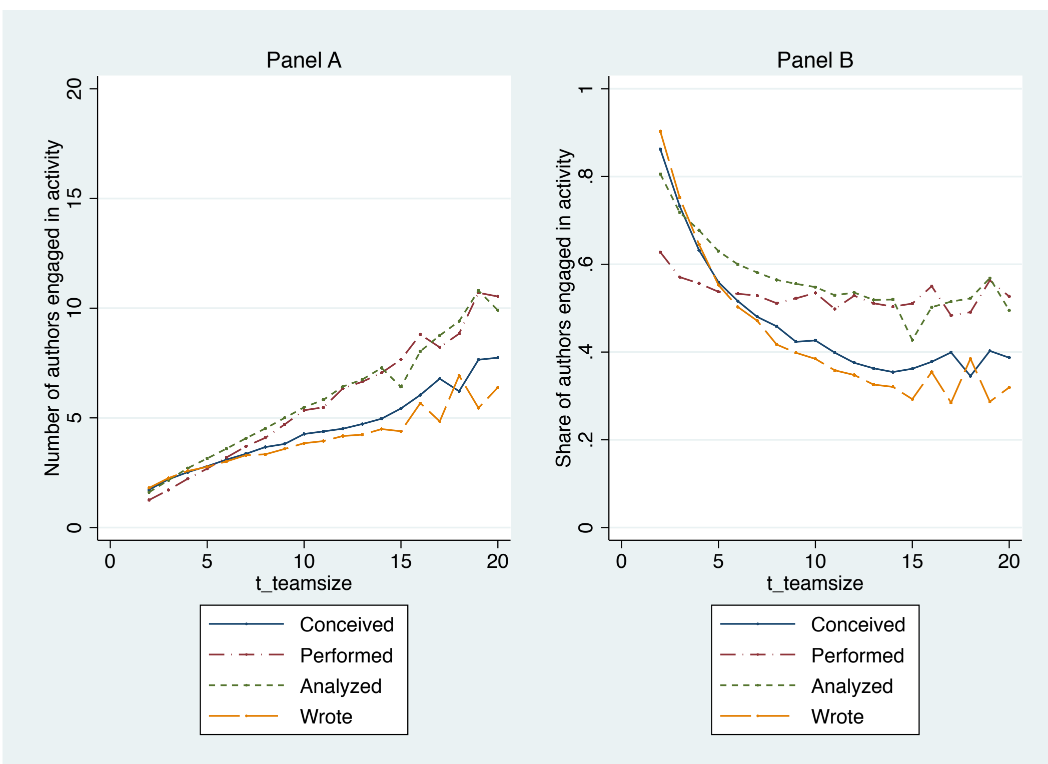
Note: Average share and count of activities per team member, and count of listed activities by team size (Panel A). Share of specialists, intermediate types, and generalists by team size (Panel B).

To explore heterogeneity across team members, Panel B plots the shares of specialists (i.e., *i_sharecontributions*<=0.2), intermediate types, and generalists (*i_sharecontributions*>0.6) in a team. The share of specialists increases 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 members do not specialize perfectly. Moreover, even large teams have generalists, 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: Count of team members performing each activity by team size (Panel A). Share 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 into discrete sub-activities that can be assigned to different team members (Von Hippel, 1990).

4.3.3 Team size in a regression framework

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 Institutes 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; the average number of field classifications is 2.50.

We also include controls for 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 U.S., 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 author affiliation is a firm.[11] Finally, we include as additional article level controls the number of pages (*t_pages)*, the publication date (*t_publicationdate*), and the number of listed contributions (up to 6, *t_totalactivitieslisted*).

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[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 frequently occurring firm names such as Pfizer or Roche.

Model 1 uses *ti_avgsharecontributions*, which is our most aggregated measure of division of labor. Consistent with Panel A in Figure 4, we find a significant negative coefficient of team size, suggesting that team members perform a smaller share of all contributions in larger teams, i.e., they are more specialized. Recall that this measure is equivalent to *ta_avgshareauthors*. 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. Consistent with Panel B in Figure 4, 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 Figure 5, we find that team size has a negative and convex relationship with all six measures. However, the size of the coefficient of team size differs across activities, with the largest negative coefficient in regressions of *a_shareconceived* and *a_sharewrote* and a smaller coefficient in the regression of *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 the division of labor across fields and types of projects

The prior sections examined patterns of division of labor across a broad sample of teams, drawing on 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 initial descriptive insights into this question by exploring differences between papers in novel vs. established

[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 Panel A in Figure 5.

fields and in interdisciplinary vs. single-disciplinary projects. While we focus on documenting potential differences, we hope that our findings will 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 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 team members in novel fields 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 also Figure 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 (Figure 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 experimental 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]

We also explore whether novel and established fields differ with respect to the correlations between different activities. Towards this end, we replicate the regressions reported in Table 2 but include interactions between *t_field_novel* and the activity dummies. Models 1-6 in Table 5 show that in novel fields, there is a somewhat weaker association between conceiving and writing, between conceiving and materials, and between conceiving and other contributions, suggesting that conceiving tends to be a more

[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 significant coefficients of *t_field_novel* also in the regressions of *a_shareconceived*, *a_shareanalyzed,* and *a_shareother*, which suggests that these activities may also be more concentrated in novel fields.

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

To proxy for interdisciplinarity, we count the number of 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%).

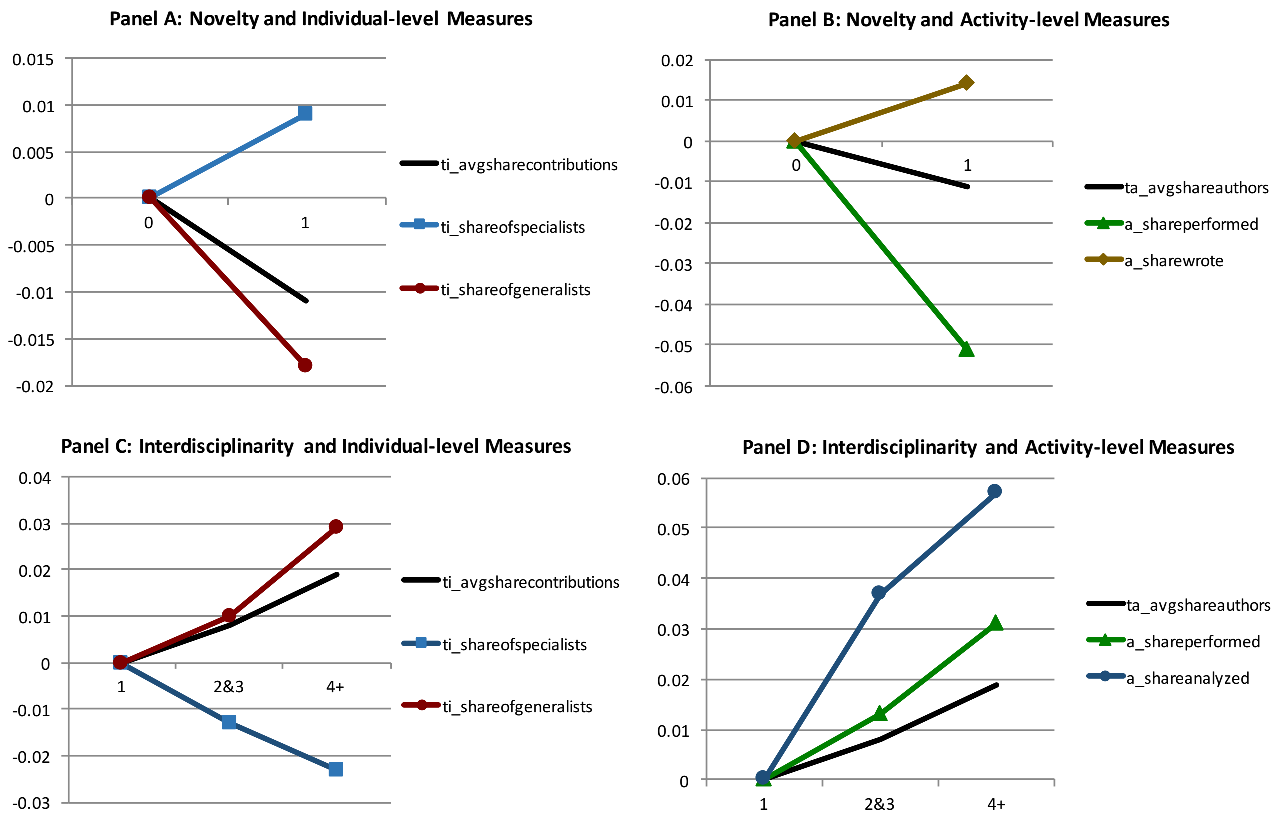
Model 1 in Table 4 shows that division of labor is lower in interdisciplinary projects (model 1), reflecting both a higher share of generalists and a lower share of specialists (models 2-4 and Figure 6 Panel C). Taking an activity level perspective, models 5-10 show that this lower division of labor reflects primarily the more distributed nature of empirical activities: Interdisciplinary projects have a significantly higher *a_shareperformed* and *a_shareanalyzed* (Figure 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. In particular, 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 highlights the more general point that division of labor with respect to activities may be different from individuals' specialization in terms of fields or knowledge domains. We will return to this issue in the general discussion.

Models 7-12 in Table 5 explore whether interdisciplinary projects exhibit different correlations between activities by interacting the field count variable with the activity dummies. We find that individuals who provide materials are more likely to also write the paper compared to single-discipline projects. At the same time, individuals who perform the experiment are less likely to also analyze data.

Taken together, our exploratory analyses show that the division of labor differs significantly between fields and types of projects, although these differences tend to be smaller in magnitude than those between teams of different size (Section 4.3). Aggregate team level measures (e.g., *ti_avgsharecontributions*) are useful to detect such differences, yet measures that allow for heterogeneity across individuals (e.g., shares of specialists and generalists) and across activities (e.g., share of members writing vs. share of members performing experiments) provide more detailed insights and can even show contrasting results (Figure 6). Future work is needed to examine the mechanisms that underlie the observed differences in the division of labor.

--- 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 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

The division of labor is often seen as a key mechanism to increase efficiency and performance. In a final set of analyses, we explore the relationship between division of labor and one particular performance measure, namely the quality of scientific output. Of course, teams can also pursue a range of other outcomes and our empirical analysis will not address potential endogeneity of team size and of the 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 proxy for the quality of scientific output using (logged) Scopus citations received by our focal papers by October 2014 (*t_lncitations*). Since citations take time to accumulate, all regressions include dummies for the month and year of publication as well as other controls such as article characteristics, field fixed effects, the number of affiliations, and the log of team members' average number of prior publications and yearly citations per paper (Table 6).

Model 1 shows the results without controls for the size of the team. 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 citations may reflect underlying differences in the size of the project. As such, model 2 flexibly controls for team size using dummy variables. We find that *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.

Model 3 provides more detailed insights by including not the aggregate measure of division of labor, but the shares of generalists and specialists (individuals with intermediate levels of specialization are the reference category and the shares of all three sum up to 100%). A higher share of generalists on the team is associated with higher citation impact. Model 4 includes the activity level measures indicating what share of team members is engaged in a given activity. Two coefficients are significant: teams in which a larger share of members is involved in performing the experiment and in writing the paper produce papers with significantly higher citation impact. We explore whether this result depends on which particular team members get involved in these activities by distinguishing between more accomplished and less accomplished team members. In model 5, we distinguish team members by whether or not they are above the (team) median in terms of average citations to their prior papers and find that papers by teams that involve a larger share of their accomplished members in writing (*t_highcitinteam_sharewrote*) have more citations. In contrast, the share of less accomplished team members involved in writing (*t_lowcitinteam_sharewrote*) has a weak negative association with citations. The share of highly accomplished team members involved in performing experiments (*t_highcitinteam_shareperformed*) has a positive coefficient, while the share of less accomplished team members involved in performing experiments has no significant coefficient. In model 6, we distinguish team members in terms of the quantity of their prior publications. A larger share of accomplished team members involved in writing (*t_highpubinteam_sharewrote*) has a positive association with citations, while none of the other variables are significant.

We can only speculate about the mechanisms underlying these results. It may be that accomplished team members who are involved in performing experiments are better able to recognize interesting and unexpected results, or that accomplished team members who are involved in writing are better able to synthesize results and to highlight the most important findings. Of course, it may also be that broader involvement by accomplished team members does not make papers better, but that accomplished team members decide to get involved more deeply in projects that appear particularly promising. Moreover, one should keep in mind that teams do not necessarily focus on maximizing the citation impact of their papers. Some teams may focus on quantity or speed rather than impact, while other teams may focus on minimizing costs (Freeman et al., 2001; Stephan, 2012). Other teams may pursue not only scientific productivity but also the training of team members (Hackett, 1990; Shibayama et al., 2015). While we cannot examine these possibilities in this paper, the analysis in this section illustrates how our framework and measures can be used to illuminate the relationships between different aspects of division of labor and different types of project outcomes.[14]

7 Discussion

Teams play a central role in many organizations and have also become important producers of new knowledge (Cummings & Kiesler, 2014; Stephan, 2012; Wuchty et al., 2007). However, little is known about how work is divided and distributed among knowledge workers. Conceptualizing knowledge production 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 insights 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 highlights 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, team level measures may be useful for some purposes, but 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 on 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; Hamilton et al., 2003; Majchrzak et al., 2012; Postrel, 2002). While much of this prior work rests on the premise that team members perform different parts of the overall task, our conceptual

[14] Given our finding of differences in the division of labor across fields and types of projects, we explored whether the relationships between division of labor and citation impact depend on field or project characteristics. More specifically, we included interactions between *t_avgsharecontributions* and the measures of novelty and interdisciplinarity in the regressions of citations but found no significant coefficients (available upon request).

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 domains rather than functional activities (Majchrzak et al., 2012; Singh & Fleming, 2010; 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 different individuals.

In addition to this conceptual contribution, we provide novel empirical insights into patterns of division of labor, drawing on a new type of publication 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 allows 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 (Bikard et al., 2015; Gittelman, 2007; Gruber et al., 2013; Singh & Fleming, 2010; Teodoridis, 2013). Even though the scientific results of teamwork are typically publicly disclosed (Dasgupta & David, 1994; Sauermann & Stephan, 2013), how these results are produced tends to remain hidden from outside observers, increasing the value of new data sources that provide insights into 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 significant 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 used to analyze differences across fields at a given point in time, it may also be useful for research on changes in the division of labor over time. Such changes 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).

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 interpretation of results largely relied on prior work explaining the division of labor from an economic and efficiency oriented perspective, yet there are several other mechanisms that may also play an important role. Among others, teams may not only pursue efficiency in the production of scientific knowledge, but also the education of team members (Hackett, 1990; Shibayama et al., 2015). Similarly, the division of labor may reflect social processes that allocate activities 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 analysis highlighted heterogeneity across team members in terms of their functional roles, we did not explore which particular members perform which activities or which particular team members emerge as specialists versus generalists. Among others, roles may be allocated based on individual characteristics such as experience, educational background, or social status (Owen-Smith, 2001; Shibayama et al., 2015). It would also be interesting to focus on particular types of individuals such as "stars", explore what they do in teams, and whether their level and type of involvement in a project shapes their impact on others or project performance (Oettl, 2012). This direction for future research is highlighted in particular by our observation that the involvement of more accomplished team members in writing and performing experiments is associated with higher citations (Section 6).

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 team members (Bikard et al., 2015; Gans & Murray, 2013; Walsh & Lee, 2015). While abstracting from team formation should not affect the value of our descriptive results, future efforts to understand the drivers of 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, simultaneous collaboration in multiple teams may allow individuals 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.

Fifth, longitudinal datasets could be used to study dynamics. At the individual level, it would be important to know whether and how scientists' degree of specialization changes over their life cycle and how flexible individuals are with respect to performing different types of activities in the same team or across different teams. At the team level, it would be interesting to observe how division of labor changes as individuals learn to collaborate or as team composition changes through entry and exit of members. At the level of scientific fields, it would be important to study how systematic changes in the size and composition of teams (Wuchty et al., 2007) are related to changes in the division of labor among team members.

Finally, it is important to explore complementarities between our activity based perspective and the view conceptualizing science as the recombination of knowledge (Simonton, 2003; Singh & Fleming, 2010; Teodoridis, 2013). One the one hand, different activities likely require different types of knowledge, and differences in knowledge stocks may explain which particular individuals perform which activities. Similarly, the observed correlations between activities may not only reflect task interdependencies and coordination costs but also that some activities draw on similar types of knowledge. On the other hand, prior work suggests that the functional division of labor can be quite different from the partitioning of knowledge (Postrel, 2002; Takeishi, 2002). Our observation that interdisciplinary projects involve lower division of labor also 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. More broadly, it is likely that different team members perform different activities drawing on different types of knowledge, and an integrated perspective that considers all three dimensions – individuals, activities, and knowledge domains – may be a particularly fruitful avenue for future research.

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 (National Academies, 2014). 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, yet common authorship guidelines typically require authors' involvement in a broader range of activities, including conceptualization or empirical work as well as 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 (Allen et al., 2014; Rennie et al., 1997). 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.

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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_priorpubs_quantity	14.99	21.99	0	200.00
i_priorpubs_quality	4.70	7.44	0	829.12
i_professionalage	12.56	10.73	0	60
i_institutionrank	5.61	2.70	1	8
i_developingcountry	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_shareananalyzed	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_avgcountcontributions	2.66	0.76	1	6
ti_avgsharecontributions	0.56	0.17	0.18	1
ti_shareofspecialists	0.16		0	0.94
ti_shareofmedspecialization	0.47		0	1
ti_shareofgeneralists	0.37		0	1
ta_avgcountauthors	3.31	1.61	1.00	16.80
ta_avgshareauthors	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_avgpriorpubs_quality	4.55	4.62	0	259
ti_avgpriorpubs_quantity	14.42	10.53	0	105
Controls				
t_totalactivitieslisted	4.80	0.68	1	6
t_affiliations	3.31	2.06	1	22
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_country_US	0.38		0	1
t_country_developing	0.09		0	1
t_pages	9.96	3.29	2	51

Note: Activity level variables (e.g., *a_shareconceived*) coded as missing if activity was not listed.

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**	0.087**	-0.041**	0.015**		-0.058**
	(0.004)	(0.005)	(0.006)	(0.005)		(0.011)
i_performed	-0.034**	0.077**	-0.192**		0.013**	-0.221**
	(0.004)	(0.005)	(0.006)		(0.005)	(0.010)
i_materials	-0.022**	-0.085**		-0.167**	-0.040**	-0.086**
	(0.004)	(0.005)		(0.005)	(0.005)	(0.012)
i_analyzed	0.244**		-0.095**	0.082**	0.079**	-0.080**
	(0.004)		(0.006)	(0.005)	(0.004)	(0.010)
i_wrote		0.306**	-0.026**	-0.042**	0.474**	-0.182**
		(0.005)	(0.006)	(0.005)	(0.004)	(0.012)
i_other	-0.163**	-0.095**	-0.126**	-0.225**	-0.051**	
	(0.009)	(0.010)	(0.014)	(0.010)	(0.010)	
i_lnpriorpubs_quantity	0.010**	-0.003	0.026**	-0.107**	0.044**	0.013**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)
i_lnpriorpubs_quality	0.009**	0.021**	0.016**	0.026**	0.011**	-0.002
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.006)
i_professionalage	0.002**	-0.005**	0.002**	-0.011**	0.003**	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
i_institutionrank	-0.008**	-0.005**	0.008**	-0.003*	-0.004**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
i_developingcountry	-0.012	-0.093**	0.052**	0.081**	0.025*	0.056**
	(0.009)	(0.011)	(0.013)	(0.012)	(0.011)	(0.019)
Constant	0.162**	0.483**	0.499**	0.898**	0.103**	0.637**
	(0.008)	(0.009)	(0.011)	(0.008)	(0.008)	(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 article fixed effects. Standard errors clustered at the level of the article. *=significant at 5%, **=significant at 1%.

Table 3: Division of labor and team size

VARIABLES	1 ti_avgshare contributions	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**	0.046**	0.062**	-0.109**	-0.097**	-0.012**	-0.062**	-0.058**	-0.108**	-0.038**
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.006)
t_teamsize_sq	0.003**	-0.001**	-0.003**	0.004**	0.004**	0.001**	0.002**	0.002**	0.004**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
t_totalactivitieslisted	-0.057**	0.094**	0.001	-0.095**	-0.034**	-0.060**	-0.038**	-0.041**	-0.047**	-0.090**
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.003)	(0.007)
t_pages	0.002**	-0.001	-0.003**	0.003**	-0.001	0.005**	0.000	0.006**	-0.002**	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
t_publicationdate	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	-0.007	0.013	-0.006	-0.004	-0.002	0.006	0.017*	-0.013*	-0.008
	(0.003)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)	(0.015)
t_funding_basic	0.008	-0.011	0.003	0.009	0.015	0.011	0.005	0.005	-0.005	0.030
	(0.006)	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.013)	(0.011)	(0.010)	(0.024)
t_funding_industry	0.008	-0.008	-0.005	0.013	0.006	0.021	-0.015	-0.001	0.009	0.048
	(0.006)	(0.010)	(0.013)	(0.011)	(0.012)	(0.011)	(0.015)	(0.013)	(0.012)	(0.027)
t_funding_other	0.000	-0.003	0.000	0.002	-0.001	0.010	0.002	-0.002	-0.014	0.038
	(0.006)	(0.008)	(0.011)	(0.010)	(0.010)	(0.010)	(0.013)	(0.011)	(0.010)	(0.024)
t_affiliations	0.004**	-0.003**	-0.001	0.004**	0.008**	-0.019**	0.013**	-0.003	0.015**	0.016**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
t_country_US	0.001	0.005	-0.008	0.003	-0.021**	0.020**	-0.000	0.015**	-0.006	-0.030*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.013)
t_country_developing	-0.013**	0.025**	-0.012	-0.012	-0.034**	0.005	-0.004	-0.000	-0.020**	-0.031
	(0.004)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.019)
Field fixed effects	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.877**	-0.201*	0.101	1.100**	0.731**	0.831**	0.789**	0.751**	0.814**	1.487**
	(0.058)	(0.088)	(0.115)	(0.102)	(0.105)	(0.099)	(0.140)	(0.115)	(0.108)	(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. Models 5-10 conditional upon activity being listed on the paper. *=significant at 5%, **=significant at 1%.

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

VARIABLES	1 ti_avgshare contributions	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**	0.009*	0.009	-0.018**	-0.009	-0.051**	0.009	-0.010	0.014*	-0.023
	(0.003)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)	(0.014)
t_numberfields_1	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted	omitted
t_numberfields_2&3	0.008**	-0.013**	0.003	0.010*	0.002	0.013**	-0.005	0.037**	-0.006	-0.006
	(0.003)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.015)
t_numberfields_>3	0.019**	-0.023**	-0.006	0.029**	0.012	0.031**	0.003	0.057**	-0.003	-0.010
	(0.004)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.019)
t_totalactivitieslisted	-0.057**	0.096**	-0.003	-0.093**	-0.033**	-0.061**	-0.036**	-0.038**	-0.049**	-0.099**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.004)	(0.003)	(0.006)
t_pages	0.001**	0.001	-0.003**	0.002**	-0.002**	0.006**	-0.001	0.007**	-0.005**	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
t_publicationdate	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	-0.005	0.012	-0.008	-0.006	-0.001	0.005	0.016*	-0.016*	-0.016
	(0.003)	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.015)
t_funding_basic	0.003	0.000	-0.005	0.004	0.011	0.018	-0.009	0.016	-0.024*	0.017
	(0.006)	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)	(0.013)	(0.011)	(0.010)	(0.024)
t_funding_industry	0.006	-0.008	-0.002	0.010	0.005	0.021	-0.022	0.002	0.003	0.054*
	(0.006)	(0.010)	(0.013)	(0.011)	(0.012)	(0.011)	(0.015)	(0.013)	(0.012)	(0.027)
t_funding_other	-0.003	0.006	-0.005	-0.001	-0.005	0.017	-0.010	0.005	-0.028**	0.032
	(0.005)	(0.008)	(0.011)	(0.010)	(0.010)	(0.010)	(0.013)	(0.011)	(0.010)	(0.024)
t_affiliations	0.005**	-0.006**	-0.000	0.006**	0.010**	-0.021**	0.017**	-0.007**	0.021**	0.021**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)
t_country_US	-0.000	0.004	-0.007	0.002	-0.022**	0.017**	-0.001	0.016**	-0.008	-0.029*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.013)
t_country_developing	-0.007	0.015*	-0.010	-0.005	-0.026**	0.000	0.000	0.000	-0.005	-0.019
	(0.004)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.018)
Team size dummies	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.734**	-0.063	0.181	0.882**	0.564**	0.774**	0.698**	0.603**	0.622**	1.372**
	(0.057)	(0.088)	(0.113)	(0.100)	(0.104)	(0.099)	(0.138)	(0.115)	(0.108)	(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. Models 5-10 conditional upon activity being listed on the paper. *=significant at 5%, **=significant at 1%.

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

	1	2	3	4	5	6	7	8	9	10	11	12
VARIABLES	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	0.001	-0.033*	-0.008		-0.094**						
	(0.010)	(0.012)	(0.015)	(0.012)		(0.028)						
int_novel_performed	0.002	0.015	0.057**		-0.012	-0.029						
	(0.009)	(0.011)	(0.013)		(0.010)	(0.022)						
int_novel_materials	0.001	0.004		0.030*	-0.016	-0.026						
	(0.011)	(0.012)		(0.013)	(0.012)	(0.028)						
int_novel_analyzed	0.013		0.006	0.016	0.004	0.016						
	(0.010)		(0.015)	(0.012)	(0.011)	(0.024)						
int_novel_wrote		0.001	-0.006	0.001	-0.021*	0.108**						
		(0.012)	(0.016)	(0.012)	(0.011)	(0.031)						
int_novel_other	0.082**	0.013	-0.039	-0.016	-0.105**							
	(0.023)	(0.024)	(0.035)	(0.023)	(0.024)							
int_numberfields_conceived							0.006	0.015	-0.006	-0.000		-0.012
							(0.007)	(0.008)	(0.010)	(0.009)		(0.020)
int_numberfields_performed							0.004	-0.020**	-0.015		-0.006	-0.030
							(0.006)	(0.008)	(0.009)		(0.007)	(0.017)
int_numberfields_materials							0.024**	-0.007		-0.005	-0.007	0.012
							(0.007)	(0.009)		(0.008)	(0.008)	(0.020)
int_numberfields_analyzed							0.002		-0.010	-0.012	0.012	0.033
							(0.007)		(0.010)	(0.008)	(0.008)	(0.017)
int_numberfields_wrote								-0.010	0.037**	-0.004	0.005	0.056*
								(0.008)	(0.011)	(0.008)	(0.007)	(0.022)
int_numberfields_other							0.046**	0.028	0.018	-0.017	-0.009	
							(0.015)	(0.016)	(0.024)	(0.018)	(0.017)	
i_conceived	0.418**	0.087**	-0.034**	0.016**		-0.039**	0.404**	0.057**	-0.029	0.015		-0.034
	(0.005)	(0.005)	(0.007)	(0.006)		(0.012)	(0.015)	(0.018)	(0.022)	(0.018)		(0.041)
i_performed	-0.035**	0.074**	-0.204**		0.016**	-0.214**	-0.042**	0.118**	-0.162**		0.025	-0.158**
	(0.004)	(0.005)	(0.006)		(0.005)	(0.011)	(0.013)	(0.016)	(0.019)		(0.015)	(0.036)
i_materials	-0.023**	-0.086**		-0.174**	-0.037**	-0.080**	-0.070**	-0.070**		-0.157**	-0.025	-0.110*
	(0.005)	(0.006)		(0.006)	(0.005)	(0.013)	(0.015)	(0.018)		(0.018)	(0.017)	(0.044)
i_analyzed	0.242**		-0.096**	0.079**	0.078**	-0.081**	0.240**		-0.075**	0.106**	0.054**	-0.147**
	(0.004)		(0.006)	(0.006)	(0.005)	(0.011)	(0.014)		(0.021)	(0.018)	(0.016)	(0.036)
i_wrote		0.306**	-0.025**	-0.042**	0.478**	-0.206**		0.326**	-0.101**	-0.034	0.463**	-0.294**
		(0.005)	(0.007)	(0.006)	(0.005)	(0.013)		(0.018)	(0.023)	(0.018)	(0.015)	(0.046)
i_other	-0.182**	-0.097**	-0.117**	-0.222**	-0.028**		-0.256**	-0.153**	-0.164**	-0.191**	-0.032	
	(0.010)	(0.011)	(0.015)	(0.011)	(0.010)		(0.031)	(0.033)	(0.051)	(0.037)	(0.035)	
Control variables	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.	incl.
Constant	0.162**	0.484**	0.499**	0.898**	0.102**	0.635**	0.162**	0.483**	0.499**	0.898**	0.102**	0.637**
	(0.008)	(0.009)	(0.011)	(0.008)	(0.008)	(0.018)	(0.008)	(0.009)	(0.011)	(0.008)	(0.008)	(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. Standard errors clustered at the level of the article. Controls: i_lnpriorpubs_quantity, i_lnpriorpubs_quality, i_professionalage, i_institutionrank, i_developingcountry. Int_ denotes interaction terms. *=significant at 5%, **=significant at 1%

Table 6: Division of labor and citation impact

VARIABLES	1 t_lncitations	2 t_lncitations	3 t_lncitations	4 t_lncitations	5 t_lncitations	6 t_lncitations
t_avgsharecontributions	-0.234**	0.155**				
	(0.048)	(0.055)				
t_sharespecialists			0.011			
			(0.037)			
t_shareintermediatespecialization			omitted			
t_sharegeneralists			0.092**			
			(0.033)			
a_shareconceived				-0.014	-0.003	-0.003
				(0.032)	(0.032)	(0.032)
a_shareperformed				0.081*		
				(0.033)		
a_sharematerials				-0.025	-0.027	-0.022
				(0.028)	(0.028)	(0.029)
a_shareanalyzed				0.005	0.002	-0.001
				(0.029)	(0.029)	(0.029)
a_sharewrote				0.121**		
				(0.032)		
a_shareother				-0.025	-0.021	-0.016
				(0.040)	(0.040)	(0.041)
t_highciteinteam_sharewrote					0.159**	
					(0.023)	
t_lowciteinteam_sharewrote					-0.051*	
					(0.025)	
t_highciteinteam_shareperformed					0.047*	
					(0.021)	
t_lowciteinteam_shareperformed					0.023	
					(0.024)	
t_highpubinteam_sharewrote						0.108**
						(0.024)
t_lowpubinteam_sharewrote						0.001
						(0.027)
t_highpubinteam_shareperformed						0.028
						(0.022)
t_lowpubinteam_shareperformed						0.046
						(0.027)
Team size dummies		incl.	incl.	incl.	incl.	incl.
Field fixed effects	incl.	incl.	incl.	incl.	incl.	incl.
ti_lnavgpriorpubs_quality	0.440**	0.426**	0.426**	0.425**	0.433**	0.429**
	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)
ti_lnavgpriorpubs_quantity	0.043**	0.049**	0.049**	0.053**	0.060**	0.058**
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
t_totalactivities	0.004	0.002	0.001	0.005	0.006	0.006
	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)	(0.015)
t_pagecount	0.035**	0.031**	0.031**	0.032**	0.032**	0.032**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
t_firm	0.040	0.022	0.022	0.023	0.021	0.018
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
t_funding_basic	0.041	0.032	0.032	0.031	0.032	0.030
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
t_funding_industry	0.048	0.015	0.015	0.015	0.025	0.018
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)
t_funding_other	0.038	0.031	0.031	0.031	0.033	0.030
	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.037)
t_affiliations	0.029**	-0.012**	-0.012**	-0.011*	-0.011*	-0.010*
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
t_country_US	0.004	0.026	0.026	0.025	0.027	0.025
	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
t_country_developing	0.020	-0.002	-0.003	-0.002	-0.002	0.000
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Publication date month/year dummies	incl.	incl.	incl.	incl.	incl.	incl.
Constant	1.894**	1.593**	1.650**	1.560**	1.511**	1.517**
	(0.145)	(0.146)	(0.140)	(0.144)	(0.145)	(0.146)
Observations	12,990	12,990	12,990	12,990	12,944	12,892
R-squared	0.224	0.240	0.240	0.241	0.242	0.239

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

APPENDIX

1 Framework with more detailed information on levels of contributions

Our basic framework required information only on whether or not an individual 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 on 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 a_{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, $S_t = \frac{\sum_{i=1}^{N} S_i}{N}$, 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**
	1	0.50	0.20		0.30	0.38
	2	0.33	0.33		0.33	0.33
Team member	**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_t): 0.50

1.2 Information on 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 what share of a given contribution was performed by each co-author.[1] Figure 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**	
	1	0.30	0.15		0.40	
	2	0.20	0.30		0.40	
Team member	**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 Information on levels of individuals' effort 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; case 1 above) as well as the share of the volume of a particular activity performed by different team members (activity level; case 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 Figure 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 can then use these shares as weights when computing the team level averages of measures of

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

specialization. More specifically, $S_{tw} = \sum_{i=1}^{N} w_i S_i$ is a team level measure of members' degree of specialization, giving more weight to members who contributed more effort to the project. Similarly, $C_{tw} = \sum_{j=1}^{K} w_j C_j$ 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)

		Activity				Sum of	Share of
		1	**2**	**3**	**4**	**indiv. effort**	**team effort (w_i)**
	1	10	2		3	15.00	0.26
	2	3	2		5	10.00	0.17
Team member	**3**			3		3.00	0.05
	4	10	4			14.00	0.24
	5	3	3	7	3	16.00	0.28
Volume of activity		26.00	11.00	10.00	11.00	**Total effort/work: 58**	
Share of total work (w_j)		0.45	0.19	0.17	0.19		

Shares of individual effort

Activity					Herfindahl-based
1	**2**	**3**	**4**	**Sum**	**S_i**
0.67	0.13		0.20	1.00	0.50
0.30	0.20		0.50	1.00	0.38
		1.00		1.00	1.00
0.71	0.29			1.00	0.59
0.19	0.19	0.44	0.19	1.00	0.30
				unweighted average (S_t)	0.55
				weighted average (S_{tw})	0.47

Shares of activity volume

	1	0.38	0.18		0.27
	2	0.12	0.18		0.45
Team member	**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_t): 0.38		
			weighted average (C_{tw}): 0.36		