When Do Researchers Collaborate? Toward a Model of Collaboration Propensity

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This exploratory study compares two approaches to understanding the "collaboration propensity" of individual researchers. On the one hand, social comparisons of disciplines would suggest that collaboration is a function of orientation toward individual versus collective responsibility for discovery. A contrasting approach would hold that collaboration depends on the work researchers are engaged in—when it is useful to collaborate, they will do so regardless of the social climate. Results presented here suggest that this latter approach is potentially more powerful but that there are complexities in measurement and operationalization that urge a more nuanced treatment of collaboration propensity.

Introduction

Collaboration in research has been a topic of significant recent interest as the scale of research projects has increased (Galison & Hevly, 1992; Price, 1963), the social networks of researchers have broadened in scope (Wagner & Leydesdorff, 2005), and there has been substantial investment in improving networking technologies that facilitate high–end computing and work in geographically distributed groups (Finholt & Olson, 1997; Hara, Solomon, Kim, & Sonnenwald, 2003; Hesse, Sproull, Keisler, & Walsh, 1993; Newell & Sproull, 1982). Moreover, recent research and reports suggest that we are presently at a crucial juncture in the development and adoption of "cyberinfrastructure" technologies for "eScience" activities (Atkins et al., 2003; Nentwich, 2003). Even as access to these technologies spreads, effective collaboration remains difficult and our understanding of it is incomplete. More specifically, collaboration must occur within a work and reward structure that is largely focused on individual achievement and reputation (Kennedy, 2003; Whitley, 2000), and coordination difficulties can impact productivity and effectiveness (Cummings & Kiesler, 2005).

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While there is a desire to address these difficulties through the improvement of cyberinfrastructure and the research environment, such action requires an improved understanding of collaboration itself, and this has been reflected in recent calls for social scientists to explore these issues (e.g., Mervis, 2005). More specifically, it is important to understand how research collaboration works and what makes it desirable to individual researchers. With an understanding of what makes collaboration desirable and useful, it becomes possible for funding agencies to invest limited resources in collaborations that are most likely to succeed and to foster conditions under which other successful collaborations are likely to take shape.

Decisions about collaboration at the individual level have been shown to depend on a range of factors, including the prior experience of participants (Hara et al., 2003), institutional constraints (Landry & Amara, 1998), the availability of "attractive" collaborators in terms of influence or unique skills (Bozeman & Corley, 2004), entrepreneurial aspirations (Oliver, 2004), and the need for access to special data or research equipment (Beaver, 2001; Kouzes, Myers, & Wulf, 1996; Melin, 2000). Some of these studies have also pointed out differences between research fields in the amount and types of collaboration observed (Bozeman & Corley; Melin), but they have not made clear the extent to which these differences result from variation in the nature of work being conducted versus social differences among fields. The present study is an exploratory move in this direction.

In the article that follows, two perspectives on collaboration are considered and compared. On the one hand, social and cultural comparisons of researchers in different disciplines (e.g., Collins, 1998; Hargens, 1975; Knorr Cetina, 1999) suggest that observed differences in collaboration behavior may be a function of socialization and particularly the extent to which individual versus collective entities are emphasized in the attribution of credit for discoveries (Knorr Cetina, 1999). On the other hand, it is possible that these cultural distinctions are epiphenomenal and that observed differences in collaboration behavior result from differences in the nature of work that scientists in different fields are engaged in. In the quantitative data presented here, this latter approach turns out to more powerful in understanding collaboration, though the qualitative data do suggest that social factors have some more subtle effects.

Research Collaboration: Background

Much research on collaboration to date has used bibliometric data (e.g., Cronin, Shaw, & La Barre, 2003; Price, 1963), sometimes using social network analysis as well (e.g., Newman, 2001; Wagner & Leydesdorff, 2005). While such techniques are useful for capturing "macro level" phenomena, Katz and Martin (1997) point out that bibliometric data are not always valid proxies for actual collaborative behavior. A few prior studies have examined collaboration at the "micro level." Hagstrom (1965) and Melin (2000), for example, suggest that collaboration is driven by the need for access to the instrumentation and expertise required to answer questions of interest. Others have investigated the relationship between spatial propinquity and collaboration, suggesting that collaboration is more likely to occur between closely collocated researchers than those who are geographically disparate (Allen, 1977; Hagstrom, 1965; Kraut, Egido, & Galegher, 1990). At the same time, however, Wagner and Leydesdorff (2005) show the growth of international collaboration networks, so propinquity is clearly not the only factor. Hara, et al. (2003) developed a preliminary framework for assessing the nature of collaborations and the conditions of their formation; but, none of these studies provide a sense of the relative weights and range of factors that influence what will be referred to here as the "collaboration propensity" of individuals.

"Collaboration propensity" is defined for the purposes of this study as the likelihood of an individual researcher engaging in collaboration at a particular point in time and with regard to current research interests[1]. Existing literature suggests that collaboration propensity is comprised primarily of two classes of attributes. First is whether researchers believe that collaboration will provide them with access to expertise, apparatus, data sets, or other resources necessary in answering research questions of interest (Beaver, 2001; Hagstrom, 1965). Second is the extent to which researchers perceive collaboration as a component of building an individual reputation and establishing a viable career path (Whitley, 2000). Collaboration propensity will serve as the dependent variable in the present study, and it will be measured using five scale items developed for this study. (See Appendix A.) The remainder of this article explores the measurement and prediction of collaboration propensity, both in terms of quantitative survey results and qualitative interviews that highlight the complexity of issues involved in thinking carefully about collaboration.

[1]This is not being treated here as a persistent character trait, though it is certainly possible that there are persistent individual attributes that influence collaboration propensity.

Predicting Collaboration Propensity: Hypotheses

In this exploratory study, the predictive power of several independent factors, each based on one of the approaches being compared, is assessed with regard to collaboration propensity.

Individual versus Collectivist Orientation

Knorr–Cetina (1999) and Collins (1998) have both pointed to social differences centered around individual versus collective responsibility for discovery in research. Knorr–Cetina, in particular, highlights differences between high–energy physics (HEP) and molecular biology, arguing that reputation in the latter field is strongly attributed to individual researchers and laboratory leaders who compete fiercely to be first author on papers and accrue reputational "credit," while the individuals she studied in HEP tended to be subsumed by large collaborative entities. This leaves open the question, however, of whether these social differences actually correlate with different attitudes toward collaboration. This question will be explored here by focusing on two issues.

Scientific Competition

Science is generally viewed as competitive in that individual researchers compete intensely in an "economy of reputation" to be the first to make unique and groundbreaking discoveries (Whitley, 2000). As Knorr–Cetina (1999) has pointed out, however, there is substantial variation in how this competition plays out. Concerns about competition and fears about being "scooped" have however been shown to impact researchers' willingness to share data (Zimmerman, 2003), adopt database systems for sharing resources even with their known collaborators (Birnholtz & Bietz, 2003), and discuss research in progress with colleagues (Blumenthal, Campbell, Anderson, Causino, & Louis, 1997; Hagstrom, 1974; Walsh & Hong, 2003). In this study, scientific competition will be measured with four questionnaire items (see Appendix A) based on those used by Walsh and Hong (2003) that ask about the extent to which scientists are concerned about discussing their results with colleagues, their concerns about being scooped, and the perceived importance of winning individual prizes and widespread recognition. It is expected that,

H1: There will be a negative relationship between collaboration propensity and the perceived level of scientific competition.

Ease of Collective Credit Attribution

Another way to consider individual versus collective responsibility is the ease with which credit can be assigned to groups of researchers. Significant contributions to research projects are typically acknowledged via authorship

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on scholarly publications, but there are differences in how this credit is assigned. Some fields of study, for example, place significant value on being the first author listed in an article (Engers, Gans, Grant, & King, 1999; Laband & Tollison, 2000); but, when there are many contributors, it may be unclear where different authors will be listed in an article. In other fields, such as HEP, all contributors are listed alphabetically on all articles. (See Birnholtz, 2006 for a detailed discussion of authorship practices in HEP.) Ease of credit attribution will be defined here as the ease with which one's coauthors can be determined when engaged in collaborative research. It will be measured using two scale items developed for this study. (See Appendix A.)

Where researchers can easily determine at the start of a collaborative project how they will receive credit for their contributions, we might expect to see differences in collaboration propensity. Thus,

H2: There will be a positive relationship between the ease of collective credit attribution and collaboration propensity.

Considering Attributes of Scientists' Work

Fuchs (1992) proposes a theory of scientific production that focuses not on the social aspects of science but on the nature of the work in which scientists are engaged from an organizational and resource coordination standpoint. An approach to collaboration propensity rooted in Fuchs's model would hold that social differences among research disciplines are epiphenomenal, and that it is the attributes of work itself that are important in understanding collaboration. Such an approach would suggest that where collaboration is useful or necessary in answering interesting research questions, we should expect to see an increase in collaboration propensity. The remainder of this section enumerates a set of constructs fundamentally rooted in Fuchs's model and outlines a second set of hypotheses.

Field–Wide Focus

Fuchs (1992), Whitley (2000), and Hargens (1975) all point to the heterogeneity of methodological approaches in a field as an important determinant of how progress in that field takes place. Field–wide focus is here defined as a measure of homogeneity with regard to research questions and methods within a field of research. It will be measured using three scale items developed for this study that ask respondents about the perceived level of agreement on methods and important research questions. (See Appendix A.) This notion is based on Fuchs' concept of task uncertainty and Hargens' concept of normative integration. Focus is low where work in a field uses a variety of methodological approaches to many loosely related research problems. This stands in contrast to fields such as HEP, where the important questions and appropriate research methods are widely agreed upon. Focus is likely to impact collaboration propensity in that people in highly focused fields will be able to work together more effectively and be more likely to find like-minded collaboration partners.

H3: There will be a positive relationship between focus and collaboration propensity.

Resource Concentration

Fuchs (1992) and Whitley (2000) both discuss the notion of mutual dependence as the extent to which researchers in a field depend on each other for access to sufficient quantities of scarce resources (e.g., funding, use of an apparatus) to be able to answer interesting research questions. Areas in which experimental and financial resources are concentrated at a small number of locations or controlled by a small group of researchers will be referred to here as having a high degree of "resource concentration." This will be measured using two scale items developed for this study that ask respondents about the extent to which research in their area requires expensive equipment or large amounts of funding. (See Appendix A.) Where resource concentration is high, researchers are likely to be dependent on others for access to these scarce experimental and financial resources (Thompson, 1967). In turn, collaboration propensity will likely increase.

H4: There will be a positive relationship between the perceived level of resource concentration and collaboration propensity.

Agreement on Quality

Another dimension of Fuchs' (1992) concept of heterogeneity is the extent to which there is agreement on what constitutes high quality research. Hargens (1975) studied several indicators of such agreement, including the rejection rates of journals, lengths of student theses, and the extent to which there were perceived hierarchies of journals and institutions. Agreement on quality is defined here as a measure of the extent to which individual researchers perceive widespread agreement on what constitutes quality research in their field of study. It will be measured here using five scale items developed for this study that ask respondents about how they assess their peers' work and about the perceptions of hierarchies of journals and institutions. Just as a high degree of focus seems likely to affect the probability of finding like-minded collaborators, widespread agreement on quality also seems likely to affect researchers' ability to find collaborators with whom they can work successfully. Thus, it is expected that

H5: There will be a positive relationship between agreement on quality and collaboration propensity.

Need for and Availability of Help

While Fuchs' theory does not directly address communication and interaction among scientists, his discussion of coordination problems does suggest the importance of effective

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interaction and coordination between researchers. As suggested by research on coordination (e.g., Malone & Crowston, 1994; Van De Ven, Delbecq, & Koenig Jr., 1976), these interactions are most important when individual work procedures are not routine and there is frequent uncertainty about how to proceed. This study therefore focuses on the amount of help–seeking behavior in which researchers engage on a day–to–day basis, as an indicator of frequent interactions and shared methodological interests. This is measured here using four scale items, based on those used by Van De Ven, et al., that ask respondents about the routine nature of their work and the amount of assistance they seek from colleagues. Where help is frequently needed and readily available, we should expect there to be more opportunities for formal collaboration.

H6: There will be a positive relationship between collaboration propensity and the need for and availability of help.

Control Variables

In addition to the factors mentioned above, there are several other demographic and basic factors that might influence collaboration propensity, such as field of study, field tenure, the usage of Internet communication and collaboration tools, and prior individual experience engaging in collaborative work. These factors will be included in this study as control variables and are discussed in detail below.

Research Context and Methods

Research Context

Researchers in the academic disciplines of earthquake engineering (EE), HEP, and neuroscience participated in this study. These disciplines were carefully selected to reflect diversity along the dimensions defined above. HEP, as discussed above and by Knorr–Cetina (1999), has a strong history of collaboration and collective credit attribution. Neuroscience, on the other hand, is more similar to the molecular biologists in Knorr–Cetina's study, as characterized by their strong emphasis on individual researchers (1999). EE is in between these two fields in terms of individual versus collective orientation. These fields also represent a diverse range of work attributes that are common to many research areas, which are described below.

High Energy Physics (HEP)

HEP has a rich history of collaborative experimental discovery that is well chronicled elsewhere (Close, Marten, & Sutton, 2002; Galison, 1997; Traweek, 1988). Experimental investigations utilize high–energy accelerators that recreate atmospheric conditions at the start of the universe. By recreating these conditions, physicists are able to generate specific particles of interest that do not occur naturally under more stable current atmospheric conditions. Large detectors are used to track the behavior and existence of these particles by recording the energy "trails" left behind. Today's accelerators and detectors dwarf all other scientific instruments. The Large Hadron Collider (LHC) at the European Organization for Nuclear Research (CERN), the world's frontier laboratory, is an underground tunnel 27 kilometers in circumference. The ATLAS (A Toroidal LHC Apparatus) detector, one of two that will sit in the LHC when it is complete in 2007, will be 20 meters in diameter and weigh 7000 tons. The human and organizational scale of this work is similarly large, with approximately 2000 physicists from institutes all over the world involved in each of the two major LHC experiments. While HEP is an admitted outlier, it is nonetheless useful to study here for two reasons. First, the community has been well–studied in the past, such that existing literature provides a useful starting point for this work and facilitates comparison. Second, large, shared instruments, facilities, and resources are increasingly common in a range of fields (Galison & Hevly, 1992; Nentwich, 2003).

Earthquake Engineering (EE)

Earthquake engineering is a field dedicated to the mitigation of earthquake risks by better understanding structural response to seismic activity and using this knowledge to modify architectural and design guidelines. Experimental research typically takes place in large laboratories using large–scale structural specimens, such as building or highway components, and specialized equipment, such as shaking platforms and steel reaction frames (Sims, 1999). Simulated seismic forces are exerted on specimens using hydraulic actuators. Investigations generally involve teams of one or two graduate students along with a faculty advisor, though there have been some instances of larger projects involving up to 10 faculty members. The specimen is generally instrumented with a large number of sensors from which numerical data that capture specimen performance can be acquired and analyzed. EE also exhibits traits common to many research fields in that it is currently focused on single–investigator research but where the scope of projects is slowly expanding; and in that the apparatus required for research are scarce, but there is increasing pressure from funding agencies to share these resources with colleagues at other institutions.

Neuroscience

Neuroscientists seek to improve treatment and prevention of mental illness by understanding the detailed workings of the brain. This is achieved primarily through laboratory work, the statistical analysis of brain activity images and, increasingly, via computational modeling of brain activity. Laboratory work is generally done by individuals in traditional laboratory spaces and involves the analysis of brain tissue from mice, primates, and humans, using gene microarrays and other techniques. It is also common to use fluorescent protein tagging techniques and transgenic animals to isolate the expression of particular genes related to specific traits and illnesses. Where collaboration occurs in neuroscience, it is

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typically undertaken to share access to or bring multiple forms of expertise to bear on the analysis and production of different aspects of rare or expensive data sets. Moreover, neuroscience is generally held to be an example of a wider set of biomedical fields of research that are highly competitive and highly focused on individual researchers (Kennedy, 2003; Knorr Cetina, 1999; "Who'd want to work in a team?" 2003).

Methods

A combination of quantitative and qualitative methods was used in carrying out this study.

Quantitative

A mail survey of 900 academic researchers affiliated with universities and government laboratories in the United States was conducted in April 2004. Three hundred researchers were randomly chosen from professional directories in each of the three disciplines under investigation and were mailed a paper questionnaire form (see Appendix A for items) to complete and return by mail. The questionnaire consisted of approximately 55 items, some of which were developed specifically for this study and others borrowed from prior work. All items had been examined and refined during two preliminary pilot studies.

Five hundred fourteen forms were returned, for a response rate of 57%, but 133 were incomplete and had to be discarded. There were no apparent differences between the completed portions of the discarded forms and the complete forms used in the analyses reported below. Response was even across the three fields and 49% of the total responses were from academic faculty. The remainder consisted of graduate students (16%), postdoctoral researchers (10%), academic research scientists (18%), and others (7%). Respondents reported receiving their highest academic degrees a mean of 14.1 years ago ($SD = 12.3$, $n = 381$), with a range of 0 to 53 years. There were no apparent demographic differences between respondents and nonrespondents.

For the purposes of the present article, only the respondents holding a Ph. D. are considered in the analyses presented below. This is to simplify interpretation and eliminate confounds related to measuring the collaboration behavior of graduate students who, because of their position, may not have the freedom to select collaborators or projects.

Prior to aggregation, the individual scale items comprising each construct were checked for reliability via a confirmatory factor analysis (Carmines & Zeller, 1979). In all cases, the items were found to load significantly onto one factor only. The individual items were then combined into aggregate construct scores by summing the individual items. Sums were used because there was no prior theoretical reason to assume that any individual item would influence the scale more than any other. The distributions of all items were checked and found to be reasonably normal. Appendix B shows the mean, standard deviation and range of values for each of the constructs. Variables were also checked for collinearity, which was not found to be a problem.

Qualitative Methods

As this is exploratory work, interviews were conducted to aid in interpreting and explaining the results. Between May 2001 and November 2004, semistructured interviews lasting 20–60 minutes were conducted with 94 researchers in the three disciplines being studied. Subjects were selected using a combination of random and snowball sampling. Thirty–two interviews were with physicists and conducted during a 10–week visit to CERN in Geneva, Switzerland. Fifty were with earthquake engineers during visits to 13 U.S. universities. The remaining 12 interviews were conducted with neuroscientists during visits to laboratories at one university and over the telephone.

Interviews were exploratory in nature at first. A similar protocol was used in each discipline but was iteratively refined as more was learned about the nature of work in each discipline. Deliberate efforts were made to speak with individuals at various points in their careers, ranging from graduate students to senior faculty and from a range of institutions.

Analysis of qualitative data consisted of careful reading and rereading of interview transcripts both before and after analyzing the quantitative data, while keeping in mind the variables described above. As themes began to emerge, transcripts were iteratively coded to reflect these themes using established qualitative methods (Miles & Huberman, 1994). These themes were then used to draw out the illustrations presented below.

Results

In this section, quantitative and qualitative results will be presented. Statistical analysis techniques are used to test the hypotheses presented above, and qualitative data are used to explain these results in greater detail.

Statistical Analyses

To analyze the survey data, a series of nested OLS regression models were used in which the independent factors were regressed on collaboration propensity (Neter, Kutner, Nachtsheim, & Wasserman, 1996). The first model used basic demographic and control variables, while subsequent variables were added one at a time (See Table 1.) The best fitting model with the largest number of explanatory factors was Model 4, with an adjusted R^2 value of .53 ($p < .01$). Model 5 is shown only to illustrate that adding additional factors added no power. Moreover, several factors are added at once in Model 5 only for illustrative purposes because none of the added factors boost the explanatory power of the model. These were added one at a time during initial analyses and had no individual effects.

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TABLE 1. Nested linear regression models predicting collaboration propensity ($N = 267$).

	1	2	3	4	5
Covariates & control					
Physics	.13*	−.03	.02	–.07	−.08
EE	−.29***	−.25***	−.26***	–.26***	−.27***
Field tenure	−.07	−.03	−.04	−.01	−.02
Coauthor (last 5 yrs)	−.01	−.05	−.09*	−.06	−.06
Remote coauthor (last 5 yrs)	.05	.02	.05	.07	.06
Successful working together	.14**	.14**	.13*	.10**	.10**
Successful results	.08	.09*	.08	.05	.05
Network tool usage	.17**	.11*	.07	.10*	.11**
Work-Related attributes					
Resource concentration		.40***	.36***	.25***	.25***
Agreement on quality			.26***	.15***	.14***
Need for and availability of help				.37***	.37***
Focus					.01
Social factors					
Standardized credit attribution					.03
Scientific competition					−.02
Adjusted R^2	.27***	.37***	.43***	.53***	.53***
R^2 change					
F Score	13.05***	42.00***	29.25***	57.08***	.22

* $p \leq .1$, ** $p < .05$, *** $p < .01$.

Do Social Differences Matter?

At a high level, this study seeks to understand whether collaboration propensity is best explained by social differences between fields or by differences in the nature of work being undertaken. Model 1, in Table 1, suggests that there are differences between fields when it comes to collaboration propensity, as the field "dummy" variables are strong predictors of collaboration propensity. As more factors are added in subsequent models, however, the predictive power of the HEP variable is gradually eclipsed. In EE, on the other hand, the dummy variable remains significant. Thus, there is mixed support for the epiphenomenal explanation of field differences in that there does appear to be some aspect of EE that is negatively related to collaboration propensity and is not effectively captured by the other variables measured here[2]. As operationalized in this study, however, social differences are measured primarily by focusing on scientific competition and ease of collective credit attribution.

Scientific Competition

Hypothesis 1 posits a negative relationship between collaboration propensity and the perceived level of scientific competition. This hypothesis was not supported by these data, as shown in Table 1. The addition of Scientific Competition in Model 5, along with other factors that had no predictive power, added no explanatory power over Model 4, and the standardized β coefficient for this variable was .02 and not statistically significant. Additional attempts to explore this surprising result by using individual scale items in place of the aggregate score yielded no meaningful results.

To be sure, this result should not be interpreted as suggesting that scientific competition does not vary or is not an important issue in the fields that were studied. Rather, it means that there is little apparent relationship between concerns about scientific competition and collaboration propensity. The qualitative data suggest two reasons for this.

First, concerns about being the first to make a discovery do not so much reduce the desire of researchers to collaborate as much as they constrain the set of possible collaborators to a few known and trusted colleagues. As one researcher said, "Collaborations are investigator initiated. And investigators aren't going to collaborate with people they think are going to stab them in the back (N2)."

This was a common feeling among informants and suggests an important distinction between collaboration and the public release of results and data that were explored in prior studies. Specifically, the freedom to choose collaborators and decide when and to whom results will be released means that concerns about secrecy have more impact on decisions about whom to collaborate with than whether to collaborate at all.

Second, several researchers had strategies for balancing individual competitive pressures with the need to collaborate. In one example, two postdoctoral researchers in neuroscience

[2]Note that only EE and HEP are included in Table 1 because "field" is a qualitative variable with multiple classes (where C = the number of classes), which Neter, et al. (1996) indicate should be represented by C–1 indicator variables. In this case, neuroscience is treated as a "reference" variable, indicated by the case where HEP and EE are both set to zero. The effects for EE and HEP technically indicate the extent to which they differ from neuroscience. Thus, we can say that EE is consistently lower in collaboration propensity than neuroscience, while neuroscience and HEP are no different from each other, after controlling for all other factors.

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reported involvement in collaborative endeavors involving rare human brain specimens but at the same time maintaining an independent line of smaller–scale research, often involving rodent specimens, to guarantee some single–author publications:

> The people that I've been exposed to with this [large collaboration] are all very well known, highly respected people that have been in the field for a long time and so there's a lot to learn from these people. But at the same time I recognize the importance of independence in this field. You're always pushed to be an independent researcher which is, of course, the role of the smaller project that I work on (N10).

Ease of Collective Credit Attribution

Hypothesis 2 predicts a positive relationship between collaboration propensity and the perceived ease of collective credit attribution. The data did not support this hypothesis. As can be seen in Table 1, the addition of this variable in Model 5 added no explanatory power over Model 4, and the standardized β coefficient was .03 and not statistically significant. Table 2 shows additionally that there does not appear to be a bivariate relationship between these variables.

Many interview subjects described situations in which clearly defined standards for credit attribution simplified the construction of author lists on articles but led to confusion and ambiguity when the terms of the collaboration where changed or where individual contributions needed to be assessed by outsiders.

HEP has a longstanding tradition of including all collaborators as authors on any article published by any member of that collaboration (Galison, 1997). In the most recent generation of completed experiments, this meant author lists that included hundreds of names. The LHC experiment author lists will include thousands of authors. On one hand, this inclusive tradition is a strong point of pride for many researchers in the field. It guarantees some degree of formal credit for everybody who contributes to a project—not just for those who happen to do the final analysis that leads to a breakthrough result.

On the other hand, though, there is an important side effect of such inclusive practices that influences people's willingness and ability to participate in collaborations. In a landscape in which the competition for jobs and promotions is fierce, the use of first– and single–authorships as a measure of individual accomplishment is essentially impossible in HEP. Thus, the value of authorship as a mark of distinction is weakened. Researchers report relying much more heavily on informal word of mouth reports about colleagues and formal letters of recommendation. Thus, even though it is clear how one will receive formal credit in the conventional sense for contributions to collaborative HEP projects, it is not clear at all how much actual reward will accrue. (See Birnholtz, 2006 for a more detailed discussion of this issue.)

In neuroscience, standards for authorship are much less formalized but no less a source of tension and confusion. Where there are multiple authors on an article in this field, it is most valuable to be the first or last author. The first author is generally the researcher who did the bulk of the work on the project and the last author is the "senior author," usually the principal investigator on the grant and the laboratory leader. This distinction works well for small groups but begins to break down with scale. In large or multisite collaborations, it may be less clear who should be listed at which position in the author list, and it is not clear what it means to be one of the "middle" authors.

> If you were the last author, the fourteenth author, the senior author then it really doesn't matter for you whether there are ten other people on it or four other people. But if you're one of those fourteen other people or one of three other people, it makes a difference (N5).

Some researchers described coping with this ambiguity by agreeing at the start of the project how authorships will be assigned. This too can cause confusion, however, as the composition of the collaboration and the nature of individual contributions can change with time. One researcher described a case, for example, where she wrote down clear rules in advance with a collaborator but a third party became involved late in the project. They then had to rewrite all of the rules, which she described as a difficult and awkward process. Indeed, the overall point here is that clear rules for credit attribution may simplify the assignment of authorships in the short term but can cause ambiguity and confusion with time.

TABLE 2. Bivariate correlations for variables of interest ($N = 267$).

	1	2	3	4	5	6	7	8
	Coll. prop.	Credit attribution	Sci. comp.	Focus	Res. conc.	Agree on qual	Help	Net. tools
1	1	.07	.06	.19***	.53***	.33***	.57***	.40***
2		1	−.08	.21***	−.07	.17***	.11*	−.07
3			1	−.04	.07	.14**	.09	.11*
4				1	.23***	.26***	.15**	.19***
5					1	.14**	.38***	.42***
6						1	.34***	.15**
7							1	.18**
8								1

$^{*}p \leqslant .1$, $^{**}p < .05$, $^{***}p < .01$.

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Considering the Nature of the Work

Hypotheses 3–7 focus on the nature of work carried out by individual researchers. As is indicated below and in Table 1, these factors were much more useful in predicting collaboration propensity than the variables in the previous section.

Focus

Hypothesis 3 predicts a positive relationship between the perceived degree of focus in a field and collaboration propensity. These data provide mixed support for this hypothesis. As can be seen in Table 2, there is a moderate positive correlation between these two variables that is statistically significant, $r = .19$, $p < .01$. Table 1, however, shows that adding Focus in Model 5 provides no additional explanatory power over Model 4 and that the standardized β coefficient is not statistically significant.

Interview informants suggested two primary reasons for this. First, the physical scale of research can play an important role in determining how much focus is necessary in a field. In HEP, for example, the scale of the experimental apparatus necessary to do work essentially mandates a shared set of research questions, goals, and methods for reaching those goals. This consensus is constrained and shaped by issues deemed important by the theoretical physics community, the state of detector technology, available funding for construction and development, and the complex political aggregation process that takes place as new experiments form. Collaboration is essential if any work is to take place at all, and there is only a scant handful of experiments in progress at any one time. Note, though, that this relationship between focus and collaboration propensity is not purely causal. Rather, scale is playing a role in driving the need for consensus and focus in the first place.

It is also important to note that HEP is an exceptional case. Most fields have far more concurrent experiments and put forth far less effort in reaching or even considering field–wise consensus with regard to important research problems and methods. As a result of this, focus can occur at multiple levels and impact collaboration propensity differently at these levels.

In the EE community, for example, the field is reasonably rigid in dividing itself into "structural" and "geotechnical" research communities. Within these subcommunities, it is far easier to find agreement on research questions and methods, but even here there are important methodological differences that could impede collaboration. Some geotechnical researchers, for example, primarily use centrifuges in their experimental work, while others do primarily field work or use large soil boxes that sit atop hydraulically actuated shaking tables. There was, however, a great deal of evidence that such differences in approach are generally viewed as complementary in the overall community. This stands in contrast to experiences described in the neuroscience community where there appeared to be more dissent about methods and definitions and less respect for alternative approaches. For example, one subject noted,

> Sure, you can get 25 people together in a room and they'll tell you, for example, that neural coding is a critical question. But if you actually sit down with each of those 25 people individually and ask them what they mean by "neural coding" they'll come up with 25 different answers (N1).

Another subject indicated with respect to his research methods that there is a large group of researchers "out there who think this is just crazy, that we really don't know enough to knock out or mutate genes and they think we're never going to learn anything" (N12). At the same time, however, the field was generally acknowledged to be large enough that researchers can find collaborators and simply avoid colleagues who do not respect their methods.

For the present discussion of focus and collaboration propensity, what all of this means is that focus is complicated and subtle—it can exist at multiple levels and relates to scale in ways that may not have been fully captured by the survey instrument used here. More study is needed to better understand this relationship.

Resource Concentration

Hypothesis 4 predicts a positive relationship between the perceived level of resource concentration and collaboration propensity. As can be seen in Table 1, Hypothesis 4 was strongly supported by these results. Adding resource concentration in Model 2 boosts the explanatory power of the model by a statistically significant difference, $F(1, 256) = 42.00$, $p < .001$. Moreover, the standardized β coefficient is consistently positive and statistically significant in all models where the variable is present. Thus, there does appear to be a positive relationship between the perceived level of resource concentration and collaboration propensity. The need for scarce resources of varying sorts appears to push researchers to work together in accumulating and accessing these resources to accomplish their goals.

In HEP and EE, the scarce resources are mostly experimental apparatus. In both fields, a scarcity of funding and experimental apparatus motivates researchers to work together. In HEP, this occurs through the pooling of research resources to construct a detector at a centralized site to which all of the contributors will then have access. This sharing is governed by a document called the "Memorandum of Understanding" that specifies contributions and is signed by a representative from each participating institute. In the EE community, experimental apparatus are generally located in a specific university laboratory and "owned" by that laboratory. The usage of these resources by "outsiders" or researchers based at other sites has traditionally required collaboration with an "insider" who has access to the equipment.

In neuroscience, much research is traditional bench science that can be done in individual laboratories. Here, the resources that must be concentrated appear to be mostly specific types of specimens that are difficult to accumulate, such as human brains, and expertise in different areas of the brain or different

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research methods. Several subjects, for example, reported specializing in very specific activities, such as one subject who indicated that he has specialized in a specific method of statistically processing functional magnetic resonance imaging (fMRI) images. He is entirely dependent on his colleagues, mostly at other institutions, to collect fMRI images and perform preliminary analyses on these. Many researchers indicated that high quality data sets are extremely costly to generate and analyze. Collaboration enables these resources to be pooled and maximally exploited.

Agreement on Quality

Hypothesis 5 states that there should be a positive relationship between collaboration propensity and the perceived level of agreement on what constitutes quality research. As can be seen in Table 1, Hypothesis 5 was supported by these results. Adding this variable in Model 3 boosts the explanatory power of the model by a statistically significant margin, $F(1, 255) = 29.25$, $p < .001$. In addition, the standardized β coefficient for this variable is consistently positive and statistically significant in all models where the variable is present. There does appear to be a positive relationship between collaboration propensity and the perceived agreement on quality. There seem to be two reasons for this: (a) in some cases, agreement is by design and supports collaboration and (b) agreement on quality allows researchers to find each other more effectively.

In HEP, there must be agreement both within and between the two large LHC collaborations that each experiment will do high quality work. Within the collaboration, this is critical in that all participating researchers must be willing to sign their names to an article announcing results in the end. When individuals fail to agree on the sufficiency of a result, subjects described systems of extensive discussion and peer review that are enacted to move the entire collaboration toward consensus. There are also procedures in place to ensure that no work is published by the collaboration that has not been carefully reviewed and "blessed" by a designated committee.

Second, there is evidence to suggest that agreement on what constitutes quality research makes researchers more aware of what their colleagues are doing and therefore better able to find collaborators. Where there is agreement, fields are less fragmented. Researchers read the same journals, attend the same conferences, and visit each other's laboratories to give talks. In some ways, this is similar to Crane's (1972) notion of the invisible college. This also provides a framework for evaluating the work of others. In neuroscience, for example, interview data suggests widespread agreement that the top journals are *Science, Nature,* and *Neuron.*

Need for and Availability of Help

Hypothesis 6 predicts a positive relationship between collaboration propensity and the need for and availability of help. As can be seen in Table 1, Hypothesis 6 was supported by these results. Adding this variable in Model 4 boosts the explanatory power of the model by a statistically significant margin, $F(1, 254) = 57.08$, $p < .001$. Additionally, the standardized β coefficient is consistently positive and statistically significant.

Generally speaking, this relationship appears to result from the proximity of researchers to each other in laboratory spaces. In the case of HEP, this effect is arguably less important causally; however, it correlates strongly in that researchers frequently see each other in the corridors and cafes at CERN but are mostly already collaborating on a large scale. In the other fields, though, proximity to noncollaborators who do similar work does appear to have an influence on the amount of help seeking that takes place and on the volume of discussions that take place that may lead to eventual collaborations.

The Role of Demographic and Control Variables

Internet–based collaboration tool usage. As can be seen in Table 1, frequent use of Internet–based collaboration tools appeared to have a positive relationship with collaboration propensity, even after controlling for all other factors. On the one hand, this is not surprising. Researchers who make frequent use of collaboration tools likely have collaborators to talk to and, therefore, have a higher propensity to collaborate. There is also evidence from a limited number of studies (Cohen, 1996; Walsh & Maloney, 2002) suggesting that the usage of computer–mediated communication (CMC) tools in research work may correlate with increased scientific productivity. The finding here serves to reinforce this prior work, but it still does not address the fundamental question of whether this relationship is causal and which way the causal arrow points. As this was not a core focus of this study, these data offer little to explain this but do point to the need for additional investigation.

Individual collaboration experience. Respondents were asked whether they had participated in collaborative research, as indicated by publishing one or more articles with coauthors within the past 5 years, and whether they had done so with remote coauthors. As can be seen in Model 1 of Table 1, these variables do not significantly predict collaboration propensity, though having a coauthor does have a slightly negative relationship with collaboration propensity in Model 3 that is statistically significant. This result is unlikely to be meaningful, however, given its brief appearance and weakness.

Respondents were also asked about the success of recent collaboration experience, both in terms of working together well and the results that were achieved. Interestingly, there is a consistently positive and statistically significant relationship between working together effectively and collaboration propensity. The same relationship is not present for success in achieving good results. This combination of results suggests that collaboration propensity depends on social relationships and the ability to work effectively together, and not just on the quality of results or having collaborated before.

Field Tenure

Bozeman and Corley's (2004) results suggest that tenure might impact collaboration propensity, depending on the "collaboration strategy" being used. On the one hand, this relationship might be positive because tenured researchers are arguably less concerned about augmenting their individual reputations. At the same time, though, it could also be negative in areas where traditional approaches to research questions call for a single–investigator model. As can be seen in Table 1, field tenure was not a significant predictor of collaboration propensity.

Research Field

It was noted above that the earthquake engineering dummy variable remained a significant predictor of collaboration propensity even after additional factors were added to the OLS models. It should also be noted that interaction effects between the field terms and each of the independent factors were tested but not found to be statistically significant or to contribute to the power of the models[3].

Discussion and Conclusion

This study began with a desire to explain observed differences in collaboration propensity. While prior studies provide strong evidence that such differences exist (Knorr Cetina, 1999; Melin, 2000), it was not clear whether these differences were best explained by social differences among researchers, or by the nature of the work being carried out. The data presented here suggest preliminarily that, in the fields studied, variance in attitudes toward collaboration is better explained by the nature of work being conducted than by the perceived individual versus collectivist orientation of a field. These results raise a number of issues with implications for how we think about and measure factors related to collaboration and collaboration propensity.

Theoretical Implications

From a theoretical standpoint, this study highlights in several respects the complexity of the lens with which collaboration propensity must be approached. In the first place, this study attempted to separate the social roots of collaboration from aspects of scientific work that may increase or decrease collaboration propensity. While this yielded some potentially useful results that are discussed below, the combined quantitative and qualitative data also have two implications for how we might measure the social aspects of collaboration.

First, we must consider the difficulties in identifying and operationalizing constructs that are reliable indicators of social differences between fields of research. While the quantitative data show few direct relationships between collaboration propensity and the social factors measured here, the qualitative data do suggest that there are some subtle and complex social influences on collaboration. Interview respondents reported being conscious of scientific competition and authorship issues in selecting collaborators, for example, but these factors served more to constrain their choice of collaborators than to influence overall collaboration propensity. This is further supported by the quantitative relationship between collaboration propensity and success with regard to working with colleagues in prior collaborations, and it suggests that there may be additional value in considering the interpersonal aspects of collaboration propensity in that researchers seemed much more likely to collaborate with some colleagues than with others. In other words, the real issue is not just generic collaboration propensity but also propensity to collaborate with a particular individual on a project.

These results also point to the likelihood of interplay between social attributes of research fields and the nature of the work in which researchers are engaged. A history of resource concentration and shared facilities in HEP, for example, seems to play a strong role in the collective orientation of the field that is evidenced in its attribution practices and focus on collective entities. At the same time, though, this relationship is not inevitable. A history of scarce, shared instruments in astronomy has not had the same effect in that astronomers tend to work on a wide range of problems and collaborate in smaller groups (McCray, 2000). Much more research is needed to better understand these relationships, but they do clearly seem to exist and are worthy of study.

Second, despite the problems in isolating and measuring the factors studied here, these results do highlight a general need to enhance our understanding of the conduct of science by looking more closely at the attributes of scientific work that impact more broadly observed phenomena, such as collaboration propensity. While field–level distinctions clearly exist, these data suggest preliminarily that there may be significant value in looking more carefully at research work at the micro level. In other words, we may be able to advance our understanding of collaboration more quickly if we focus our investigations on researchers with similar styles of work rather than use fields as boundaries.

Such a shift provides the additional benefits of allowing consideration of the work attributes studied here more carefully and in providing a forum for identifying and isolating components of research disciplines that may be important to collaboration but that were not specifically measured here. In some ways, this general need echoes claims previously made by Vaughan (1999) and Barley (1996) who call for a more careful consideration of the organizational setting of knowledge creation and work. By moving from high–level studies of science to more detailed and systematic studies

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[3]These interaction effects were tested for using methods suggested by Jaccard, Turrisi and Wan (1990). The product terms of each field dummy variable and each predictor variable were regressed on collaboration propensity, but the model yielded no statistically significant increase in predictive power, $F(16, 233) = 1.38$, $p = .15$.

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of scientific work, we can draw on an extensive literature of individual motivations and group or organizational behavior and information processing. Such an approach, particularly as collaboration and the development of collaboration tools become increasingly important will arguably allow for a more valuable and nuanced understanding of collaboration.

Practical Implications

From a policy standpoint, the lack of explanatory power for certain attributes of the individual versus collectivist orientation of the research environment provides some indication that when considering collaboration tools and their adoption, certain concerns about scientific competition as an impediment may be unwarranted. Indeed, a focus on supporting existing collaborative groups, respect for privacy and allowing them to grow and evolve may be enough to overcome perceived potential cultural barriers. Researchers to whom collaboration is valuable may overcome these barriers on their own, and tools should be made readily available to these researchers as well.

Additionally, these results provide a strong suggestion that there were work conditions under which attitudes toward collaboration were more positive. In particular, this was true in areas where resources were highly concentrated (e.g., at CERN in the extreme case), where there was strong agreement on what constitutes high–quality research, and where colleagues were available and consulted when help was needed. While it is not possible to attribute causality based on these data, this does indicate that these are circumstances under which collaboration may be more likely to occur. This reinforces prior suggestions, for example, that much collaboration begins with informal interactions between those who are proximate (Allen, 1977; Kraut et al., 1990). Thus, there continues to be likely value in providing facilities, both physical and online, to support informal interaction that may lead to collaboration.

At the same time, this is not to suggest that merely concentrating the resources in a field will result in increased collaboration in that field. This sometimes appeared to occur in the fields studied here because there were no or few viable alternatives. It is difficult, for example, to break away from collaboration as a high–energy physicist and do single–investigator research because specialized equipment is necessary. The same is not true, for example, in the social sciences, where it is much easier to do research without specialized equipment. Thus, concentrating social sciences resources may not have the same impact on collaboration behavior.

It is finally important to bear in mind, however, that these results also provide some limited evidence suggesting that considering only the nature of the science, and ignoring social differences, will not always work. The consistently negative relationship between being an earthquake engineer and possessing collaboration propensity indicates that, at least in EE, there may be some as–yet–unmeasured components of culture or work that might further inhibit collaboration.

Limitations and Future Work

Limitations

As suggested above, a major limitation in this work is the difficulty of effectively measuring social and cultural factors related to collaboration propensity, and of isolating these factors from work–related attributes. There are two primary problems. First, it is difficult to select the correct social factors and to define these in a way that can be measured. Two factors were chosen here that have been highlighted in prior research. However, the fact that there was still a statistically significant effect for the EE field on collaboration propensity suggests that there are other social attributes of the fields studied that influence collaboration propensity but were not adequately measured here. This suggests that more research is needed to better operationalize and capture these.

Second, there is the problem that the work–related attributes clearly eclipsed the social factors in the quantitative results, but it is not clear whether this was the purely the result of explanatory power or, as is more likely, also due in part to the difficulties of accurately measuring cultural and social motivators of human behavior. As was mentioned above, scientific competition and attribution practices do seem to be related to collaboration propensity, but the relationships are not always clean or direct. This suggests that there may be better ways to capture these factors, and to capture additional factors that may have a more substantial influence on collaboration propensity, perhaps via more sophisticated measurement and modeling.

Moreover, there is an implicit assumption here that collaboration propensity, as measured here, corresponds to actual collaboration behavior. While this was not verified in the context of the present study, this could conceivably be done by, for example, tracking the number of coauthored works published by the individuals in the sample for some future time period. At the same time, however, the variety of items used to measure collaboration propensity and the face–to–face contact with many of the respondents in interviews do suggest that this construct is at least reasonably reliable. This is another area for potential future investigation however.

Additional Directions for Future Research

As mentioned above, this study highlights the complexity of the lens through which collaboration must be considered and, in particular, the difficulty of accurately measuring issues related to collaboration propensity. If we are to engage in the sort of systematic analysis that will allow us to understand the conditions under which collaboration is likely to occur and succeed, then we must improve our ability to accurately measure both social and work–related attributes of science that are related to collaboration. Moreover, it may not always be possible for survey respondents to fully articulate the motivations for their behavior or the conditions of work in their area. Thus, we should consider the development and usage of psychometric techniques that allow for inference of attitudes toward work and collaboration through patterned responses to novel questionnaire items (similar to personality inventories used by psychologists). This sort of work can be combined with bibliometric and other analyses to derive a much more nuanced understanding of collaboration propensity.

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Appendix A

Questionnaire Items and Factor Component Scores

Variable	Item wording	Factor analysis component scores*
Agreement on quality	When I assess the work of my peers, I use the same standards that they use in assessing my work	.53
Agreement on quality	When I assess the merits of a peer's research, my assessment is generally in agreement with my peers.	.64
Agreement on quality	When my work is reviewed by my peers, I generally agree with their assessment.	.56
Agreement on quality	There is a clear hierarchy of journals in my field, with leaders that are generally agreed upon throughout the field	.65
Agreement on quality	There is a clear hierarchy of universities in my field, with leaders that are generally agreed upon by most researchers	.49
Availability of and need for help	I frequently come across specific, difficult problems in my work that I do not know how to solve alone.	.61
Availability of and need for help	In doing my day-to-day research work, I use a standard set of methods that could also be applied to other problems or tasks.	.54
Availability of and need for help	When I encounter a difficult problem in my work, I seek the advice of a colleague or mentor	.69
Availability of and need for help	Most other researchers in my field use techniques or methods similar to the ones that I use	.61
Collaboration propensity	Collaboration with other researchers would benefit my career.	.54
Collaboration propensity	Other researchers in my field who do collaborative work are successful.	.62
Collaboration propensity	I plan to engage in collaborative research in the future.	.74
Collaboration propensity	Collaboration is necessary in my field	.69
Collaboration propensity	Collaboration is useful in solving problems that are of interest to me	.81
Credit attribution practices	When I participate in a research project, it is clear at the start of the project how I will receive credit for my contribution to the work (i.e. via an authorship on a publication, etc.)	.81
Credit attribution practices	When I publish an academic paper, it is easy to determine whom to include as coauthors on the work	.81
Focus	The methods I use in my research are the only methods used for legitimate research in my field	.64
Focus	There are methods used by some prominent researchers in my field that I do not believe yield valid results even when they are used correctly	.51
Focus	There is widespread agreement in my field about what the important research questions are	.73
Resource concentration	Doing cutting edge research in my field requires access to rare and expensive equipment	.75
Resource concentration	Producing quality research in my field requires access to an amount of funds that it might be difficult for a single investigator to secure	.75
Scientific competition	I feel safe in discussing my current work with other persons doing similar work (other than my collaborators)	.48
Scientific competition	I am concerned that the results of my current research might be anticipated or "scooped" by other scientists working on similar problems.	.63
Scientific competition	The competition for prizes or widespread recognition in my field is intense	.30
Scientific competition	In the past 5 years, the results of my research have been anticipated or "scooped" by other scientists working on similar problems	.45

Note. * A separate factor analysis was run for each variable. In all cases, principal components analysis was the extraction method and a single component was extracted.

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Appendix B

Descriptive Statistics

Descriptive statistics by field ($N = 267$).

	Physics ($N = 103$)				EE ($N = 91$)				Neuro ($N = 73$)				Total	
Variable	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Mean	SD
Collaboration propensity	16.00	25.00	22.06	2.07	14.00	25.00	19.34	2.33	15.00	25.00	21.10	2.44	20.87	2.54
Scientific competition	5.00	17.00	11.64	2.49	6.00	19.00	11.76	2.42	4.00	18.00	11.84	2.95	11.73	2.60
Credit attribution	2.00	10.00	7.47	1.58	4.00	10.00	7.69	1.28	3.00	10.00	7.19	1.52	7.47	1.47
Focus	4.00	13.00	8.87	1.58	4.00	11.00	7.65	1.49	4.00	10.00	7.21	1.33	8.00	1.64
Need for and availability of help	11.00	20.00	16.72	1.72	9.00	20.00	15.63	2.01	10.00	20.00	15.78	1.94	16.09	1.94
Agreement on quality	14.00	23.00	19.00	1.81	13.00	25.00	18.85	2.18	12.00	24.00	18.86	2.15	18.91	2.03
Resource concentration	4.00	10.00	9.57	.98	3.00	10.00	7.30	1.80	3.00	10.00	7.86	1.77	8.33	1.83

Note. All variables were measured using 5-point Likert scales, but different numbers of item scores were summed to create these constructs. Thus, the value ranges for these variables differ. Overall maximum and minimum values are not provided in the 'total' column because these can be easily determined by looking for the smallest or largest value in each row.

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