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Collaboration experiences across scientific disciplines and cohorts

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Abstract Even though there is a rich discussion in the literature about co-authorship practices, many of the existing studies do not offer a dynamic picture of co-authorship patterns and experiences across disciplines. To address the research gap, our study aims to explore several key dimensions of the social dynamics in co-authorship practices. In particular, we examine cohort differences in collaboration patterns across disciplines and cohort differences in negative collaboration experiences across disciplines. To conduct our analyses, we use data from a national survey of scholars and engineers in 108 top research universities. Our results indicate that the number of collaborators at one's own university is correlated with an increase in negative collaboration experiences, while an increase in collaborators at other universities is not correlated with an increase in negative collaboration experiences. In addition, we conclude that junior scholars are more likely to have negative collaboration experiences than their senior peers. This result is true even after controlling for gender and discipline.

Keywords Research collaboration · Collaboration patterns · Collaboration experiences · Cohort differences · Scientific disciplines

Introduction

Despite the extensive literature focused on scientific collaboration patterns and experiences, few of these studies offer a dynamic picture of patterns and experiences across disciplines (Bozeman et al. 2015; Youtie and Bozeman 2014). Instead, many of these

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studies utilize a bibliometric analysis of co-authorship patterns, based typically on the numbers of coauthors, coauthored papers or citations (for an overview of literature see Glänzel et al. 2006). For example, several studies have used bibliographic data from online databases to examine the structures, dynamics, and evolution of research collaboration networks across disciplines (Ferligoj et al. 2015; Kronegger et al. 2012, 2015; Mali et al. 2012). While bibliometric analysis is demonstrably useful and important for understanding collaboration, such measures are not always able to capture the full range of social dynamics experienced in research collaboration.

Within this context, we define social dynamics as the norms, practices, and ethical issues within the research collaboration process (Youtie and Bozeman 2014). In previous studies, the key variables measuring the social dynamics of research collaboration have focused on collaboration experiences (e.g., Bozeman et al. 2015; Youtie and Bozeman 2014), ethical problems in research co-authoring (e.g., Bozeman and Youtie 2015; Marušić et al. 2011), and variations in co-authorship network (De Stefano et al. 2011; Liu et al. 2005; Uddin et al. 2013). In line with these earlier studies, we believe that negative collaboration experiences across scientific disciplines and cohorts represent a key dimension of the social dynamics of research collaboration that is not well addressed in previous research.

The goal of our study is to address some of these issues in the literature by using survey data to explore the social dynamics of co-authoring teams with a particular focus on the quality of collaboration experiences. Since it is well known that practices and outcomes are affected by disciplinary norms and traditions, we give particular attention to variations by discipline. Also, given that norms change and collaboration experiences vary with career progression, we consider the effects of career cohorts on collaboration outcomes. Our study is focused on three research questions. First, across scientific disciplines, how is the physical location of collaborators related to negative collaboration experiences? Second, across scientific disciplines, how is the sector affiliation (i.e., public, private, government) of collaborators related to negative collaboration experiences? Third, across scientific disciplines, what are the cohort differences in negative collaboration experiences?

In our study, we draw from the research collaboration literature that is focused on spatial proximity, sector difference and cohort differences in collaboration experiences. To fully answer our above research questions, we have used the existing literature to create three hypotheses that we can test with our dataset. First, we expect that closer spatial proximity will be associated with fewer negative collaboration experiences; moreover, we expect that cross-sector collaborations will be associated with more negative collaboration experiences. Second, we expect that junior scholars will have more negative collaboration experiences than senior scholars.

Our study has three main contributions to the literature. First, albeit disciplinary differences in collaboration practices, our analyses highlight negative collaboration experiences as one key dimension of social dynamics of research collaboration. Second, our analyses show that spatial distances and sector differences are not necessarily associated with negative collaboration experiences. Third, our analyses demonstrate that across different disciplines, junior scholars do experience more negative collaboration experiences than senior scholars.

In the next section of this article, we link these hypotheses to the existing literature. Then, we discuss our data collection process and describe our variables and measurement strategy. After that, we present the results of our analyses to report the results of our hypothesis testing. In the final section, we discuss several implications of our findings for scientific collaboration scholarship, as well as limitations of this study and future directions.

Collaboration and scientific disciplines

Research collaboration within and across disciplines

Within the scholarly literature, co-authorship is the most frequently used indicator of collaboration (Bozeman et al. 2013; Glänzel and Schubert 2004; Katz and Martin 1997; Laudel 2002; Melin and Persson 1996; Subramanyam 1983). Co-authorship has become increasingly common in academic fields in recent decades (Adams et al. 2005; Katz and Martin 1997; National Science Board (NSB) 2014; Sonnenwald 2007). Indeed, collaboration and co-authorship have become the norm in scientific and technology research communities (Beaver and Rosen 1979; Bozeman et al. 2013; Lee and Bozeman 2005; Moody 2004). More than 94 percent of recently published, peer-reviewed papers in science and engineering fields have two or more authors (Bozeman and Boardman 2014). This trend is visible across different disciplines (Cummings and Kiesler 2005; Laband and Tollison 2000; Newman 2001a, b; Schummer 2004), such as physics (Albert and Barabási 2002; Braun et al. 1992; Newman 2004), chemistry (Glänzel and Schubert 2001), biomedical research (Albert and Barabási 2002; Bordons et al. 1996; Newman 2004; Shapiro et al. 1994), and economics (Barnett et al. 1988; Goyal et al. 2006; Hudson 1996; Maske et al. 2003). For example, mathematicians traditionally focused on producing single-authored papers, but they are more willing to published coauthored papers in recent years (Brunson et al. 2014; Genest and Thibault 2001; Newman 2004). Social sciences and humanities fields, which typically have lower co-authorship rates than the natural sciences, have also demonstrated an increase in co-authorship patterns over time (Cronin et al. 2003; De Stefano et al. 2011; Endersby 1996; Larivière et al. 2006; Lewis et al. 2012; Moody 2004; Ossenblok et al. 2014; Wuchty et al. 2007). For example, Web of Science data shows that the percentage of single-authored papers in the social sciences has dropped from 72 percent in 1981 to just 38 percent in 2012.[1] Moody (2004) reports that co-authorship rates in the field of sociology have increased from 31 percent (1975–1985) to 38 percent (1989–1999). Likewise, in the field of economics, a typical economist on average had less than one coauthor (0.894) in the 1970s, and the average number of coauthors has increased to 1.244 (1980s) and then 1.672 (1990s), showing a relatively small but consistent trend of growth in research collaboration (Goyal et al. 2006).

Despite the widespread use of co-authorship as a measure for collaboration, many scholars have highlighted the limitations associated with the argument that co-authorship equals collaboration (Bozeman et al. 2013; Katz and Martin 1997; Melin and Persson 1996). For example, co-authorship does not capture the whole picture of collaboration activities (Katz and Martin 1997; Laudel 2002; Van Raan 1998); rather, it represents a specific type of collaboration that lists the names of collaborators in an article (Katz and Martin 1997). At the same time, bibliometric data based on coauthored papers leads to only a partial understanding of collaboration patterns (Calvert and Patel 2003). For example, bibliometric studies tend to use co-authorship as the primary indicator for collaboration, resulting in a systematic bias against other forms of collaboration practices (Laudel 2002). In short, coauthored articles are not the only output that research collaboration produces, and co-authorship does not guarantee the existence of collaboration because some coauthors may have no contribution at all (Melin and Persson 1996). There could be additional problems related to the bibliometric method of collecting publication data from online databases. For example, the author name disambiguation issue (such as homonymy and

[1] http://sciencewatch.com/articles/single-author-papers-waning-share-output-still-providing-tools-progress.

synonymity) makes the search for co-authorship information difficult and possibly inaccurate (Calero et al. 2006; De Stefano et al. 2013; Kang et al. 2009). Additionally, online databases that collect information about journal articles and books fail to cover other types of scientific output, such as reports, monographs, and creative works (Hicks 1999). These limitations should be taken into account when using co-authorship to measure research collaboration.

However, there can also be significant advantages of using co-authorship for measuring collaboration; these include issues such as verifiability, dataset stability over time, relatively inexpensive data collection costs, access to large databases of co-authorship records, and ease of measurement (Katz and Martin 1997; Subramanyam 1983). Partly because of these advantages, co-authorship remains one of the primary measures of collaboration within the existing scholarly literature. Given these advantages—and to compare our results with existing literature findings—we use co-authorship as one measure of collaboration in this article. However, this is not the only measure of collaboration that we utilize in our study. We will address how our use of survey data can supplement co-authorship data in our data collection section.

In terms of social dynamics of research collaboration, collaboration frequency within and across disciplines only capture part of the whole picture. Another important (but less well-developed) topic revolves around researchers' collaboration experiences. Drawing from the literature, we develop our research hypotheses pertaining to negative collaboration experiences.

Research hypotheses

The process of publishing multi-authored papers entails considerable effort, cost and negotiation among multiple individuals and organizations (Cummings and Kiesler 2007; Katz and Martin 1997; Melin 2000). Therefore, collaboration is not always a positive experience and it can often lead to a negative outcome for scholars (Bozeman et al. 2013). Several scholars point out that collaboration can bring up issues of trust, unequal author order, and other contentious issues in the coauthoring process (Bennett and Taylor 2003; Rennie et al. 1997; Riesenberg and Lundberg 1990). To summarize some of these negative collaboration experiences, Bennett and Taylor (2003, p. 266) define a set of authorship irregularities, including honorary or guest authorship (someone who does not desire authorship credit), pressured authorship (the misuse of seniority to gain undesired authorship credit) and ghost authorship (someone who desires credit but did not appear in the author list).

There are also some disciplinary differences in collaboration within the literature. For example, biomedical scholars have traditionally paid more attention to unethical authorship practices than other disciplines (e.g., Flanagin et al. 1998; Ross et al. 2008; Wilcox 1998). The discussion about these authorship disputes and ethical issues in other fields is less visible. For example, in a systematic review of the literature on authorship issues, Marušic et al. (2011) find that two-thirds of the studies of unethical authorship practices are from biomedical and health research fields, while only one-third of the studies are from natural science and social science fields. Clearly, negative collaboration practices constitute an important part of the co-authorship process and should be addressed during a discussion of disciplinary differences in collaboration. Thus, there is a need for linking disciplinary co-authorship patterns and negative collaboration experiences. This leads to our first research question: Across scientific disciplines, how is the physical location of collaborators related to negative collaboration experiences?

Even though the existing literature that is focused on collaboration experiences across disciplines is somewhat sparse, we have developed some hypotheses for this section based on the literature that addresses issues of spatial and sector proximity for collaboration. For example, existing research demonstrates that when two potential collaborators are farther apart in spatial proximity, they are less likely to collaborate and communicate (Bozeman and Corley 2004). Despite the reduced costs associated with long-distance collaboration because of internet and technology advancement (Frame and Carpenter 1979; Stefaniak 2001; Van Raan 1998; Wagner and Leydesdorff 2005), close spatial proximity tends to encourage collaboration because of more opportunities of informal communication (Hagstrom 1965; Katz and Martin 1997; Kraut and Egido 1988). Similarly, Katz (1994) finds that increasing distances between collaborators in different institutions result in a decrease in co-authorship. Geographical proximity is therefore an important factor influencing inter-regional research collaboration (Liang and Zhu 2002). Moreover, researchers in developing (peripheral) countries might strategically choose to collaborate more with developed (core) country scholars than with neighbor country counterparts in order to gain advanced knowledge and funding opportunities (Kim 2006; Schubert and Sooryamoorthy 2010). For example, recent data show that South Africa's top three collaboration partners are the USA, UK, and Germany, and the only neighbor country in its top twenty partners is Nigeria (Schubert and Sooryamoorthy 2010). A few studies have called into question the importance of geographical proximity for collaboration and knowledge interaction (Howells 2002; Malmberg and Maskell 2002; Torre and Rallet 2005). Some of these studies argue that geographical proximity serves only an indirect role in collaboration—and that it does not necessarily guarantee a successful collaboration (Boschma 2005; Howells 2002). Yet, an overview of the studies regarding the spatial aspects of collaboration (Frenken et al. 2009) demonstrates that "physical proximity indeed affects scientific interaction patterns" (p. 228). By examining data on co-authorship in 33 European countries, Hoekman et al. (2010) found that researchers prefer to collaborate with those who are in physically closer locations, even though European integration has made interaction across territorial borders easier.

Additionally, the impact of spatial proximity can vary across different inter-organizational collaborations. Ponds et al. (2007) explored science-based technologies in the Netherlands and they found that academic and non-academic organizational collaboration needs more spatial closeness than purely academic collaboration, which means geographical proximity can help overcome institutional or sector differences. This literature is related to our second research question: Across scientific disciplines, how is the sector affiliation (i.e., public, private, government) of collaborators related to negative collaboration experiences?

Given the above mentioned literature, we have developed a series of testable hypotheses to address our first and second research questions. We expect that closer proximity collaborations will yield more positive collaboration experiences because of the ease of knowledge exchange and, in particular, reduced transaction costs. Thus, we also expect that as scholars collaborate outside of their institution (i.e., university) and outside of their sector (i.e., academia), they will be more likely to have negative collaboration experiences. These expectations are reflected in our hypotheses.

H1 For all disciplines, negative collaboration experiences will increase as scholars collaborate with others who are more distant from them (both spatially and by sector)

H1a For all disciplines, as scholars have more coauthors at their same university, they will have fewer negative collaboration experiences

H1b For all disciplines, as scholars have more coauthors at a different university, they will have more negative collaboration experiences

H1c For all disciplines, as scholars have more coauthors in non-university sectors, (i.e., with private industry or firms), they will have more negative collaboration experiences

Now we will turn to our third and final research question. This question asks: across scientific disciplines, what are the cohort differences in negative collaboration experiences? Since much of the existing literature is focused on collaboration intensity and frequency (rather than collaboration experience), our hypotheses about negative collaboration experiences are not solely drawn from the literature. Rather we utilize both the literature (when appropriate) and our previous case study research (Boardman and Bozeman 2007; Corley et al. 2006) to develop hypotheses about cohort differences in negative collaboration experiences.

Even though few scholars have explored the link between negative collaboration experiences and career age, some scholars have studied cohort trends over time for research collaboration (without an explicit focus on negative collaboration experiences). While some existing studies have used age as a control variable (Cainelli et al. 2012), others have explored how career age is related to scientists' productivity and co-authorship patterns (Badar et al. 2014; Dietz and Bozeman 2005; Lee and Bozeman 2005; Levin and Stephan 1991). For example, O'Brien (2012) concluded that a junior cohort (i.e., graduated between 1983 and 1991) had a higher co-authorship rate in their early career publications than a senior cohort (i.e., graduated between 1953 and 1962). In addition, some studies have empirically demonstrated that junior scholars are more productive than their senior colleagues (Rauber and Ursprung 2008). Yet, the idea that senior scholars have lower productivity is contradicted with other studies (Hamermesh 2013; Levin and Stephan 1991). For example, the age distributions of authors in top economic journals over the past 60 years demonstrate an increasing percentage of senior authors (Hamermesh 2013).

In light of these existing studies, we expect to observe some significant differences in collaboration experiences across different cohorts. Given the current trend of collaboration as the norm in many disciplines, research collaboration today is like "a rite of passage" for junior scholars (Hara et al. 2003, p. 957). We speculate that this trend could mean that junior scholars are expected (and required) to collaborate instead of choosing to collaborate, which could lead to more negative collaboration experiences. Additionally, senior scholars often have the power to distort authorship order and credits (Drenth 1998). Bennett and Taylor (2003) argue that junior scholars may feel pressured to give senior scholars undeserved credit in order to get published easier or repay favors for funding and research opportunities. Kwok (2005) argues that there is a potential for a "white bull" effect, which means senior scholars may abuse or bully junior scholars by distorting co-authorship credits or conducting deceptive behaviors. However, negative collaboration experiences can also happen between scholars at similar ranks or in faculty-student collaborations (Fine and Kurdek 1993). Drawing from this literature, we have developed our second hypotheses.

H2 For all disciplines, junior scholars will have more negative collaboration experiences than their senior colleagues

Now we discuss our data collection, measurement details, and the results of our hypothesis tests.

Data collection

As mentioned earlier, we are supplementing co-authorship data with survey data in this article. These survey data results allow us to explore details about collaboration patterns and experiences that we would not capture by just focusing on co-authorship data. Since we use survey data for our analyses, we are able to measure collaboration as co-authorship, but also we measure the social dynamics of collaborative teams and disciplinary differences in collaboration norms and practices. The source of our dataset is a web survey (part of a National Science Foundation-funded multiyear research) of 641 non-medical academic researchers in Science, Technology, Engineering and Math (STEM) disciplines in 108 Carnegie Doctoral/Research Universities—Very High Research Activity category (more details about data and procedures are available in Youtie and Bozeman 2014). A sampling frame of science and technology fields was developed using NSF's categories in its Survey of Earned Doctorates. In addition, economics was included in the sample as a social sciences discipline that could be compared with the other STEM fields. Therefore, the sampling frame is based on 14 disciplines and sub-disciplines in biology, chemistry, computer science, mathematics, engineering, and economics. The choice of economics as a comparison was pragmatic. The grant supporting this research provided funds to study STEM fields, not social science fields. Yet, we had a strong interest in including at least one social science comparison field and this was accepted by the funding agency. Economics was chosen because many of the practices in economics contrast with the sciences and engineering (e.g., the tendency to provide credit by alphabetic order).

The sampling frame called for one male and one female faculty member from each randomly selected department at a given university because previous qualitative interviews suggested that gender would be a significant factor. In the event that no female faculty members were affiliated with the department, two male researchers were selected. The target sampling frame resulted in 2996 faculty members. We were able to collect contact information for 2,574 individuals in the sampling frame. Out of this number, 2189 were of sufficient quality as indicated by an electronic mail verification software program. We conducted pilot surveys in April and May 2012 with 400 faculty members. This left 1789 faculty names for the final survey. Six waves of survey invitations and reminders were sent in October and November 2012. One percent of respondents were not at their office location, while another five percent explicitly opted-out of participation. In all, we received 641 completed or mostly completed online questionnaires, for a 36 percent response rate. Respondents were similar to the population in terms of gender, rank and departmental discipline. Given that we oversampled females and certain departments, we re-weighted results to reflect the population distribution as indicated in the NSF Survey of Doctorate Recipients 2006 (most recently available survey).

However, as with all survey data collection, there are some caveats. First, the re-weighting that we utilized was straightforward, simply adjusting observations in direct proportion to the percentage of women in each disciplinary category (as determined through the NSF Survey). Since some possibility of (low levels) of gender-based measurement bias remains, results must be treated with caution. Second, it is certainly desirable to have a response rate of greater than 36 percent. However, we note that many online surveys receive smaller response rates, often around 25 percent (Millar and Dillman 2011). Increasingly, scientists in the US are declining to response to survey requests and, thus, possibilities for response bias increases accordingly. However, we have no evidence that selection effects are in this case distorting and, moreover, the fact that the percentages of respondents track well against known population parameters is encouraging.

In next section we discuss the measurement of negative collaboration experiences and cohort differences.

Measurement

For this study, we measured negative collaboration experiences in two contexts: (1) for the respondents' full career and (2) for their most recent article. The survey questions for both of these concepts are summarized in Table 1.

Table 1 Summary of negative collaboration experience variables

Negative collaboration experience time frame	Survey question response categories	Survey question	Survey question use as dependent variable
For full career	0 = never happened 1 = 1–3 times 2 = more than 3 times For the models in Table 8, response categories were recoded for use as binary dependent variables: 0 = never happened; 1 = happened at least once	A co-author did not finish agreed upon research-related activities	*T* test in Table 3; *T* test in Table 7; Model 1 in Table 8
		Co-authorship credit was denied to someone who deserved to be a co-author	*T* test in Table 3; *T* test in Table 7; Model 2 in Table 8
		A co-author claimed lead authorship when it was not deserved	*T* test in Table 3; *T* test in Table 7; Model 3 in Table 8
		A person listed as a co-author made no contribution at all to the research	*T* test in Table 3; *T* test in Table 7; Model 4 in Table 8
For most recent article	1 = strongly disagree to 10 = strongly agree For the models in Table 6, response categories were recoded for use as binary dependent variables: 1–5 = 0 and 6–10 = 1	All things considered, I feel my contribution was greater than my co-authors	*T* test in Table 4; correlation analysis in Table 5; Model 1 in Table 6; *T* test in Table 9
		There is at least one person who deserved co-author credit but did not receive it	*T* test in Table 4; correlation analysis in Table 5; *T* test in Table 9
		There is at least one person who did not deserve co-author credit but received it	*T* test in Table 4; correlation analysis in Table 5; Model 2 in Table 6; *T* test in Table 9

For the full career of a researcher, we asked respondents four questions and they answered with numbers from 0 to 2 (0 = has never happened; 1 = 1–3 times; 2 = more than 3 times). Respondents were asked if they have experienced any of the following negative collaboration experiences during their career: (1) a coauthor did not finish agreed upon research-related work; (2) co-authorship credit was denied to a deserved person; (3) a coauthor claimed undeserved lead authorship; and (4) a person made no contribution at all to the research, but was listed as a coauthor. For the logistic regression models in Table 8, we have recoded full career negative collaboration experience variables (three categories) into dichotomous variables (0 = never happened; 1 = happened at least once).

As for the most recent article, we asked respondents three questions with a Likert response scale (1 = strongly disagree; 10 = strongly agree). The three questions were the following: (1) All things considered, I feel my contribution was greater than my co-authors, (2) There is at least one person who deserved co-author credit but did not receive it, and (3) There is at least one person who did not deserve co-author credit but received it.

A portion of our analysis in this study is focused on exploring collaboration differences across cohorts. To complete this analysis, we defined junior and senior cohorts based on the year that respondents received their Ph.D. degree. We used the median value for Ph.D. year (i.e., 1995) as the threshold between the junior and senior scholars. Therefore, the respondents in the senior cohort are those who received their Ph.D. degrees before or during 1995. The respondents in junior cohort are those who received their Ph.D. degrees after 1995.

Table 2 Descriptive statistics ($N = 642$)

	Mean (SD)
Demographic variables	
Male (percent)	46.7
Respondents' age	48.2 (11.8)
Race/ethnicity	
Caucasian (percent)	77.1
Asian (percent)	13.2
Hispanic (percent)	4.4
African American (percent)	1.6
Native American (percent)	0.2
Other Race (percent)	0.7
Missing/No response (percent)	2.8
Career variables	
Year Ph.D. Awarded	1993.7 (11.7)
Years Since Ph.D. Awarded	18.31 (11.7)
Tenured (percent)	66.4
Academic rank	
Assistant professor (percent)	25.2
Associate professor (percent)	20.6
Full professor (percent)	49.7
Other positions (percent)	3.6
Missing rank—no response (percent)	0.9

Results

Before delving into the results of our hypothesis tests, we will first outline some of the demographic characteristics of our survey respondents. As shown in Table 2, the percentages of men and women are roughly equivalent in our sample (due to the stratification of our sample). For other variables, the respondents are similar to the demographic characteristics of the population of STEM academic faculty, perhaps somewhat younger and more junior because of the overrepresentation of women. The percentage of non-Asian minorities remains small (less than 10 percent) as is the case with the population.

Disciplinary differences in collaboration patterns

In this section, we will discuss the disciplinary differences that we observed for the respondents' collaboration patterns. Since previous studies have demonstrated the

Table 3 Collaboration comparisons for *Full Career* across disciplines ($N = 642$)

	Life sciences ($n = 62$)	Physical sciences ($n = 178$)	Engineering ($n = 314$)	Math ($n = 50$)	Economics ($n = 38$)
Demographic variables (mean values)					
Tenured (percent)	75.81	67.42	63.69	68.00	65.79
Male (percent)	50.00	50.00	42.04*	50.00	60.53
Year Ph.D. was awarded	1989.02**	1992.60	1995.54**	1991.28	1994.44
Caucasian (percent)	93.55**	82.58*	69.11**	90.00*	73.68
Asian (percent)	3.23**	9.00*	18.79**	2.00**	18.42
Collaboration patterns for full career (mean values)					
Percentage of published work single-authored	8.93	7.42*	6.57**	24.50**	37.89**
Percentage of co-authored papers including students	58.60	64.94	74.92**	15.88**	24.84**
Negative collaboration experiences for full career (mean values) (0 = has never happened; 1 = 1–3 times; 2 = more than 3 times)					
A coauthor did not finish agreed upon research	0.97	0.97*	0.82	0.71	0.86
Co-authorship credit was denied to someone who deserved it	0.18	0.18	0.21	0.08*	0.11
A coauthor claimed lead authorship when it wasn't deserved	0.32	0.33	0.39*	0.10**	0.24
A coauthor made no contribution at all to the research	0.43	0.57	0.57	0.44	0.24**
Sum of four indicators of negative collaboration experiences (Cronbach's $\alpha = 0.56$)	1.87	2.05	1.97	1.33**	1.47

Significance tests represent independent samples t tests for those within the discipline reported versus all other respondents. For example, for "Life Sciences" the two groups compared were: Life Scientists (Group 1) and All Other Disciplines (Group 2)

Respondents could choose multiple race categories so percentages may be greater than 100

* Significant at the 0.05 level

** Significant at the 0.01 level

Table 4 Collaboration patterns for *Most Recent Article* across disciplines ($N = 642$)

	Life sciences ($n = 62$)	Physical sciences ($n = 178$)	Engineering ($n = 314$)	Math ($n = 50$)	Economics ($n = 38$)
Collaboration patterns for most recent article (mean values)					
Number of coauthors affiliated with respondent's university	2.22	2.37	2.19	1.20**	1.07**
Number of coauthors at a different university	3.69	8.57*	1.53**	1.28	0.94
Number of coauthors in a private firm or industry	0.13*	0.23	0.47**	0.08**	0.11**
Negative collaboration experiences for most recent article (mean values) (1 = strongly disagree; 10 = strongly agree)					
I feel my contribution was greater than my coauthors	4.08	4.57	4.73	4.88	4.92
There is at least one person who deserved coauthor credit but did not receive it	1.31	1.39	1.50	1.06**	1.05**
There is at least one person who didn't deserve co-author credit but received it	2.10	2.13	2.35	1.65*	2.38
Sum of three indicators of negative collaboration experiences (Cronbach's $\alpha = 0.46$)	7.48	8.06	8.57	7.59	8.35

Significance tests represent independent samples *t* tests for those within the discipline reported versus all other respondents. For example, for "Life Sciences" the two groups compared were: Life Scientists (Group 1) and All Other Disciplines (Group 2)

* Significant at the 0.05 level

** Significant at the 0.01 level

importance of disciplinary differences in collaboration patterns, we highlight those here before moving on to the results of our hypothesis tests. The collaboration variables listed in Table 3 cover the respondent's full career, while the collaboration variables in Table 4 are focused only on the respondent's most recent published article.[2]

As Table 3 demonstrates, engineering scholars display a more diverse ethnic composition with the lowest percentage of Caucasian respondents (69.11 percent) and the highest percentage of Asian respondents (18.79 percent). Economics scholars have the second lowest percentage of Caucasian respondents (73.68 percent) and the second highest percentage of Asian respondents (18.42 percent). One caveat here is that minorities may be underrepresented because our sampling criteria were focused on the variables of gender and departmental discipline. Since older respondents have more experience than younger respondents for the full career questions (simply because of the longer career span), we control for years since Ph.D. degree when we introduce a multi-variate analysis later in the article.

[2] Due to questionnaire design, we only have data for number of coauthors affiliated with respondent's university, at a different university, at a firm or industry for the most recent article (Table 4). Therefore, in Tables 3 and 6 we do not have data for number of coauthors with different affiliations.

The collaboration results in Table 3 illustrate that faculty in engineering fields display the lowest rate of single-authored articles (6.57 percent). Across the remaining four disciplinary fields, life scientists (8.93 percent), physics scientists (7.42 percent) and math scholars (24.5 percent) display a lower rate of sole-authored papers than do economists (37.89 percent). The above results correspond with the existing literature which states that natural scientists and engineers are more likely to coauthor articles than scholars in social sciences and humanities (Larivière et al. 2006; Moody 2004; Stefaniak 2001). Yet, as we mentioned earlier, some existing studies demonstrate an increasing trend of co-authorship among social science researchers (Barnett et al. 1988; Hudson 1996; Maske et al. 2003).

As Table 3 shows, engineering scholars are likely to collaborate with students, with about 75 percent of their work being co-authored with students. Scholars in the life sciences and physical sciences published about 59 and 65 percent of their papers with students, respectively. On the other hand, mathematicians only publish about 16 percent of their papers with students. This result is consistent with previous studies that have highlighted how mathematics scholars have somewhat different patterns of collaboration than other STEM researchers (Bozeman and Corley 2004; Franceschet and Costantini 2010; Genest and Thibault 2001).

Negative collaboration experiences

As Table 3 illustrates, over the course of their career mathematicians are less likely than scholars in other disciplines to have experienced a coauthor with undeserved lead authorship or a coauthor that was not given deserved co-authorship credit. We expect that this result is (at least partly) an artifact of the low collaboration rates that we observe among math scholars. In other words, as scholars collaborate less, they likely have fewer negative collaboration experiences. In addition, our analysis demonstrates that physics scholars are more likely to have a coauthor who did not finish agreed upon research, while engineers are more likely than other scholars to have experiences undeserved lead authorship.

While Table 3 was focused on collaboration across the respondent's full career, Table 4 is focused only on collaboration for the respondent's most recent article. By focusing on the most recent article, we are able to analyze our data without the complicating factor of different career lengths. The results in Table 4 show that respondents in mathematics and economics have fewer coauthors affiliated with their university than their peers. In addition, while mathematics scholars have the lowest number of coauthors affiliated with private industry, engineers have the highest number. Physical scientists are more likely to than their peers to have coauthored their most recent article with scholars at a different university.

Table 4 also provides summary results about negative collaboration experiences for the respondent's most recent article. The results illustrate that mathematics and economics scholars are less likely than their peers to have experienced a coauthor not receiving deserved credit on their most recent article. Also, mathematics scholars are less likely than their peers to have experienced a coauthor receiving undeserved credit. We expect that these results for mathematics scholars and economics scholars can be partly explained by the fact that scholars in these two fields have fewer coauthors on their most recent article than their peers.

Hypothesis 1: Collaboration experiences by coauthor affiliation

Our first hypothesis focuses on capturing linkages between negative collaboration experiences and distance from collaborators. We hypothesize that as researchers have more coauthors at their own university, they will have fewer negative collaboration experiences (hypothesis 1a). On the other hand, we expect that as researchers have more coauthors at a different university, they will have more negative collaboration experiences (hypothesis 1b). Furthermore, we expected to see more negative collaboration experiences for those respondents who worked with coauthors from other sectors, such as private industry or firms (hypothesis 1c).

Tables 5 and 6 illustrate our bivariate and multivariate (respectively) analyses for testing our hypotheses about coauthor affiliation. We should note that for the analysis in Table 6, we converted the negative collaboration experience variables for the most recent article into a binary variable to use as the dependent variable in our logistic regression model. The details of our recoding are outlined in Table 1. Also, for the models in Table 6, we recoded the coauthor affiliation variables to measure the presence (recoded as a 1) or absence (recoded as a 0) of a coauthor at the same university, different university or industry. We believe that this analysis provides a complement to the bivariate analysis in Table 5, which uses the full scale for the number of coauthors at each affiliation. Additionally, there is one negative collaboration experience variable in Table 5 that is not included in Table 6 (i.e., the statement: "There is at least one person who deserved coauthor credit but did not receive it.") This statement is not included in Table 6 because the model was not significant. The model summary statistics for this dependent variable were the following: −2 Log likelihood = 58.06; Chi Square = 8.01 (sig = 0.156). Since the model did not yield a significant Chi Square value, we are not reporting the results in Table 6.

Table 5 Correlation matrix for collaboration patterns and experiences for *Most Recent Article* ($N = 642$) (values in table: Spearman's rho)

	I feel my contribution was greater than my co-authors	There is at least one person who deserved coauthor credit but did not receive it	There is at least one person who didn't deserve co-author credit but received it
Negative collaboration experiences (1 = strongly disagree; 10 = strongly agree)			
# of Coauthors—same university all disciplines	0.05	0.08*	0.13**
# of Coauthors—different university all disciplines	−0.07	0.02	0.05
# of Coauthors—private firm all disciplines	0.13*	<0.01	0.09

* Spearman's rho is significant at the 0.05 level

** Spearman's rho significant at the 0.01 level

*** Too few observations to compute correlation

Table 6 Binary logistic regression model for negative collaboration experiences across *Most Recent Article*

	B	SE	Wald	*df*	Sig.	Exp (*B*)
Model 1: Dependent Variable ("All things considered, I feel my contribution was greater than my co-authors")[a]						
Male	−0.575	0.281	4.195	1	0.041	0.563*
Years since Ph.D.	−0.035	0.014	6.501	1	0.011	0.966*
Coauthor affiliation						
Same University[c]	−0.096	0.322	0.089	1	0.765	0.908
Different University[d]	0.118	0.311	0.145	1	0.703	1.126
Industry[e]	1.162	0.391	8.857	1	0.003	3.197**
Constant	−0.21	0.408	0.264	1	0.608	0.811
Model 2: Dependent Variable ("There is at least one person who didn't deserve co-author credit but received it")[b]						
Male	−0.206	0.386	0.284	1	0.594	0.814
Years since Ph.D.	−0.056	0.021	7.078	1	0.008	0.946**
Coauthor affiliation						
Same University[c]	1.014	0.487	4.333	1	0.037	2.758*
Different University[d]	0.456	0.409	1.241	1	0.265	1.577
Industry[e]	1.4	0.452	9.594	1	0.002	4.055**
Constant	−2.28	0.592	14.838	1	<0.001	0.102**

Disciplinary field is not included in these models because it was not significant for negative collaboration experience for the most recent article

* Significant at the 0.05 level

** Significant at the 0.01 level

[a] -2 Log likelihood $= 328.55$; Chi Square $= 24.37$ (sig < 0.001)

[b] -2 Log likelihood $= 196.53$; Chi Square $= 21.82$ (sig $= 0.001$)

[c] Was there at least one person at same university who was a coauthor on the article? (0 = No;1 = Yes)

[d] Was there at least one person at a different university who was a coauthor on the article? (0 = No;1 = Yes)

[e] Was there at least one person in industry who was a coauthor on the article? (0 = No;1 = Yes)

Lastly, we do not include discipline as a control variable in the models in Table 6 because they are not significant for negative collaboration experiences focused on the most recent article. Disciplinary field is an important variable for analyzing negative collaboration experiences over the full career so we keep it in our analysis for those full career variables (in Table 9). Yet, we do not include discipline in the results for Table 6 because they are not significant in any of the models. Now we will move to discussing our results for hypothesis 1a-1c using the analysis in Tables 5 and 6.

For hypothesis 1a, the bivariate analysis did not yield the results that we expected. As Table 5 demonstrates, we find that as the number of coauthors at the respondent's own university increases, the number of negative collaboration experiences (having at least one person not receiving deserved credit and having at least one person receiving undeserved credit) also increases. Before drawing a final conclusion, however, we also wanted to test this relationship while controlling for gender and career age (or years since Ph.D.).

Model 2 in Table 6 yields a similar result. The value of exp (B) gives the change in the odds ratio for each one-unit increase of the independent variable. Exp (B) with values greater than 1.000 indicate that an increase in one unit of the independent variable is associated with an increased probability of the dependent variable. By contrast, if the value of exp (B) is less than 1.000, a decreased odds ratio comes with a one-unit increase in the independent variable. We use Model 2 as an example to illustrate our results. For this model, we find that having a coauthor at the same university increases the odds that a respondent would experience the negative collaboration experience (in this case, having at least one person not deserve credit but receive it) by 2.758 times. We did not find a significant relationship between the negative collaboration experience in Model 1 and the presence of a coauthor at the same university. Based on the results from Tables 5 and 6, we must reject our hypothesis 1a. Our data indicate that in some cases having a coauthor at the same university does not affect the likelihood of a negative collaboration experience—and in other cases it is correlated with an increase in negative collaboration experiences.

Now we can move to the results for hypothesis 1b. Based on the results from the bivariate analysis in Table 5, we should reject this hypothesis because we do not find a significant relationship between number of coauthors at a different university and negative collaboration experiences. The results are similar for Table 6. We do not find a significant relationship between negative collaboration experiences and the presence of coauthors at another university for Model 1 or Model 2.

Hypothesis 1c explores the relationship between cross-sector collaborators (in particular, collaborations with industry or private firms) and negative collaboration experiences. The results in Table 5 demonstrate that our test of hypothesis 1c yields mixed results. A higher number of industry coauthors is correlated with an increase in respondents' perceptions that their contribution is greater than their coauthors. Yet, the other two collaboration experience variables (having at least one person who did not receive deserved credit and having at least one author who received undeserved credit) are not significantly correlated with number of private firm coauthors. Table 6 yields even stronger results. For both Models 1 and 2, we find that the presence of an industry-based coauthor increases the likelihood of a negative collaboration experience (i.e., Model 1: feeling that personal contribution was greater than coauthors and Model 2: having at least one person not deserve credit but receive it). Given the results from Table 6, we cannot reject hypothesis 1c.

We would like to note that our dataset does not include the variables about coauthor affiliation (i.e., affiliation with the respondent's university, a different university, and industry) over the respondent's full career. We only have these variables for the most recent article. Therefore, we can test hypotheses 1a-c for the most recent article (as we have in Tables 5 and 6), but we cannot test them for the full career with our existing dataset. We believe that these variables will be important for inclusion in future data collections to test these hypotheses for a longer time span.

Hypothesis 2: Collaboration Experiences by Cohort and Career Age

Our second hypothesis is focused on collaboration experiences across different career ages or cohort groups. For one part of our analysis (presented in Tables 7 and 9), we split our dataset into two cohorts based on the year that respondents received their Ph.D. degree. We use the median value for Ph.D. year (i.e., 1995) as the threshold between the junior and senior scholars. Respondents in the senior cohort received their Ph.D. degrees before or during 1995, while respondents in junior cohort received their Ph.D. degrees after 1995.

On the other hand, for our regression analyses (presented in Tables 6 and 8) we do not use the two cohort groups; instead we use a control variable that measures the number of years since the Ph.D. degree. First we will test our hypothesis for the variables across the respondent's full career (i.e., Tables 7 and 8). Then we will test the hypothesis for variables that are focused only on the most recent article (i.e., Tables 6 and 9).

Table 7 demonstrates that the junior cohort is less likely to be tenured (not surprisingly) and less likely to be male. Also, there are fewer Caucasians and more Asian respondents in the junior cohort when compared with the senior cohort. Furthermore, in line with increasing levels of collaboration across many disciplines in recent years, we found that the junior cohort has a significantly lower percentage of sole authored articles (6.62 percent) than their senior colleagues (13.49 percent). Also, respondents in the junior and senior cohorts were equally likely to have published coauthored articles with students.

Tables 7 and 9 show some summary data results for the two cohorts for collaboration patterns and experiences across the full career and for the most recent article, respectively. Specifically, Table 7 demonstrates that across the full career, the junior cohort is more

Table 7 Collaboration comparisons for *Full Career* across cohorts for all disciplines ($N = 623$) (T test results; test variable: senior cohort versus junior cohort)

	Senior cohort mean ($n = 312$)	Junior cohort mean ($n = 311$)	T value
Demographic variables			
Tenured (percent)	96.79	39.55	19.40**
Male (percent)	59.94	35.37	6.44**
Caucasian (percent)	85.90	72.03	4.57**
Asian (percent)	7.37	19.94	−4.65**
Collaboration patterns—full career			
Percentage of Published Work Single-Authored	13.49	6.62	4.32**
Percentage of Co-authored Papers Including Students	62.79	64.77	−0.66
Negative collaboration experiences—full career (0 = has never happened; 1 = 1–3 times; 2 = more than 3 times)			
A coauthor did not finish agreed upon research	0.88	0.86	0.33
Co-authorship credit was denied to someone who deserved it	0.15	0.21	−1.75
A coauthor claimed lead authorship when it wasn't deserved	0.29	0.39	−2.35*
A coauthor made no contribution at all to the research	0.44	0.61	−3.14**
Sum of four indicators of negative collaboration experiences (Cronbach's $\alpha = 0.56$)	1.75	2.07	−2.54*

Senior cohort: Scholars receiving Ph.D. degree before and during 1995 (median value)

Junior cohort: Scholars receiving Ph.D. degree after 1995 (median value)

19 respondents did not report Ph.D. Year so they are missing from the cohort analysis

Significance tests represent independent samples t tests. The two groups that were compared were: Senior Cohort (Group 1) and Junior Cohort (Group 2)

* t test significant at the 0.05 level

** t test significant at the 0.01 level likely to have experienced (1) a coauthor claiming lead authorship when it was not deserved; (2) a coauthor contributing nothing to the paper; and (3) a higher summative index of negative collaboration experiences. These results confirm our second hypothesis.

Table 8 Binary logistic regression model for negative collaboration experiences across *Full Career*

	B	SE	Wald	*df*	Sig.	Exp (*B*)
Model 1: Dependent Variable ("A co-author did not finish agreed upon research-related activities")[a]						
Male	−0.373	0.185	4.078	1	0.043	0.689*
Years Since Ph.D.	0.006	0.008	0.498	1	0.480	1.006
Life Sciences	0.629	0.318	3.911	1	0.048	1.876*
Physical Sciences	0.812	0.219	13.692	1	0.000	2.253**
Mathematics	0.071	0.325	0.048	1	0.827	1.074
Economics	0.169	0.372	0.206	1	0.650	1.184
Constant	0.492	0.177	7.743	1	0.005	1.635**
Model 2: Dependent Variable ("Co-authorship credit was denied to someone who deserved to be a coauthor")[b]						
Male	−0.199	0.227	0.768	1	0.381	0.820
Years Since Ph.D.	−0.021	0.010	4.212	1	0.040	0.979*
Life Sciences	−0.038	0.369	0.011	1	0.917	0.962
Physical Sciences	−0.198	0.254	0.610	1	0.435	0.820
Mathematics	−0.937	0.545	2.957	1	0.086	0.392
Economics	−0.683	0.553	1.526	1	0.217	0.505
Constant	−0.933	0.210	19.756	1	<0.001	0.393**
Model 3: Dependent Variable ("A co-author claimed lead authorship when it was not deserved")[c]						
Male	−0.209	0.189	1.228	1	0.268	0.811
Years Since Ph.D.	−0.012	0.008	2.096	1	0.148	0.988
Life Sciences	−0.150	0.310	0.235	1	0.628	0.860
Physical Sciences	−0.114	0.208	0.299	1	0.585	0.892
Mathematics	−1.415	0.490	8.340	1	0.004	0.243**
Economics	−0.553	0.421	1.725	1	0.189	0.575
Constant	−0.368	0.180	4.204	1	0.040	0.692*
Model 4: Dependent Variable ("A person listed as a coauthor made no contribution at all to the research")[d]						
Male	−0.223	0.175	1.621	1	0.203	0.800
Years Since Ph.D.	−0.023	0.008	8.934	1	0.003	0.977**
Life Sciences	−0.162	0.293	0.305	1	0.581	0.850
Physical Sciences	−0.038	0.196	0.038	1	0.846	0.962
Mathematics	−0.072	0.323	0.050	1	0.823	0.930
Economics	−1.102	0.422	6.819	1	0.009	0.332**
Constant	0.362	0.171	4.492	1	0.034	1.437*

* Significant at the 0.05 level

** Significant at the 0.01 level

[a] −2 Log likelihood = 761.54; Chi Square = 20.57 (sig = 0.002)

[b] −2 Log likelihood = 561.76; Chi Square = 13.26 (sig = 0.039)

[c] −2 Log likelihood = 735.96; Chi Square = 18.65 (sig = 0.005)

[d] −2 Log likelihood = 818.92; Chi Square = 23.99 (sig = 0.001)

This result was somewhat surprising since the junior cohort has a shorter career span (and, therefore, less time to have negative collaboration experiences). In fact, we expected the opposite result for Table 7 because we do not control for Ph.D. year in this table. For this reason, we will control for years since Ph.D. degree in our regression analysis (in Table 8).

To control for discipline and years since Ph.D. degree we also conducted a series of multi-variate analyses focused on the full career negative collaboration variables. For this analysis, we conducted four binary logistic regression models. Each model utilized one of the four survey statements about negative collaboration experiences over the full career as a dependent variable. We chose this model because it allowed us to explore the relationship between career age and negative collaboration experiences while controlling for gender and disciplines. This analysis allowed us to test our second hypothesis in a more refined way.

For the binary logistic regression models, we first prepared our four dependent variables by recoding the four negative collaboration statements for the full career (please see Table 1 for the full career collaboration variables and their response categories). The first statement corresponds to the dependent variable for Model 1 in Table 8 (i.e., "A co-author did not finish agreed upon research-related activities"). The second statement corresponds to the dependent variable for Model 2 in Table 8 (i.e., "Co-authorship credit was denied to someone who deserved to be a co-author"). The third statement corresponds to the dependent variables for Model 3 in Table 8 (i.e., "A co-author claimed lead authorship when it was not deserved"). The fourth (and final) statement corresponds to the dependent

Table 9 Collaboration patterns for *Most Recent Article* across cohorts for all disciplines ($N = 623$) (T test results; test variable: senior cohort versus junior cohort)

	Senior cohort mean ($n = 312$)	Junior cohort mean ($n = 311$)	T value
Collaboration patterns			
Number of coauthors affiliated with respondent's university	2.09	2.14	−0.27
Number of coauthors at a different university	5.02	2.47	1.52
Number of coauthors in a private firm or industry	0.39	0.25	1.56
Negative collaboration experiences (1 = strongly disagree; 10 = strongly agree)			
I feel my contribution was greater than my coauthors	4.16	5.13	−4.24**
There is at least one person who deserved coauthor credit but did not receive it	1.30	1.45	−1.31
There is at least one person who didn't deserve co-author credit but received it	1.89	2.52	−3.21**
Sum of three indicators of negative collaboration experiences (Cronbach's $\alpha = 0.46$)	7.33	9.11	−4.62**

Senior cohort: Scholars receiving Ph.D. degree before and during 1995 (median value)

Junior cohort: Scholars receiving Ph.D. degree after 1995 (median value)

19 respondents did not report Ph.D. Year so they are missing from the cohort analysis

Significance tests represent independent samples t tests. The two groups that were compared were: Senior Cohort (Group 1) and Junior Cohort (Group 2)

* t test significant at the 0.05 level

** t test significant at the 0.01 level variables for Model 4 in Table 8 (i.e., "A person listed as a co-author made no contribution at all to the research"). The original questionnaire response categories for all four of these statements were the following: 0 = never happened; 1 = 1–3 times; 2 = more than 3 times. For our binary logistic regression analysis, we recoded these three response categories into two categories (i.e., 0 = never experienced and 1 = experienced at least once). This allowed us to use the new binary variables as the dependent variables in our four models in Table 8.

In Table 8, we present the results of all four models. In Model 1, being a life sciences scholar increases the odds that a respondent would experience the negative collaboration experience (in this case, not having a coauthor finish agreed upon research-related activities) by 1.876 times or 87.6 percent. However, the life sciences discipline is not the only significant independent variable in Model 1. Being a physical sciences scholar increases the odds that a respondent would experience the negative collaboration experience (in this case, not having a coauthor finish agreed upon research-related activities) by 2.25 times. Moreover, males are less likely than females to have a co-author who did not finish agreed upon research-related activities (exp (B) = 0.689). This means that being male decreases the negative collaboration experience odds by 31.1 percent. Finally, Model 1 does not indicate a significant relationship between career age and the likelihood of having a coauthor not finish agreed upon research activities). Therefore, this model does not confirm our second hypothesis.

In Model 2, however, career age is significantly related to the likelihood of a respondent experiencing the denial of co-authorship to someone who deserved to be a co-author (exp (B) = 0.979). In this case, a one unit increase in years since the Ph.D. degree decreases the negative collaboration experience odds by 2.1 percent. For this model, gender and discipline were not significantly related to the likelihood of a respondent experiencing the denial of co-authorship to someone who deserved to be a co-author. In sum, Model 2 does confirm our second hypothesis for the negative collaboration experience of the denial of co-authorship credit.

As with Model 1, Model 3 does not confirm our second hypothesis. We do not find a significant relationship between career age and a coauthor claiming lead authorship when it was not deserved. This result was somewhat surprising for us. However, we did find some disciplinary differences for this model. In particular, being a mathematics scholar decreases the odds of experiencing this type of negative collaboration experience by 75.7 percent (exp (B) = 0.243).

As with Model 2, Model 4 does confirm our second hypothesis. For this model, the negative collaboration experience was expressed as a person being included as a coauthor when they made no contribution to the research. In this case, a one unit increase in years since the Ph.D. degree decreases the negative collaboration experience odds by 2.3 percent (exp (B) = 0.977). For this model, gender was not significantly related to the likelihood of a respondent experiencing undeserved co-authorship. However, being an economics scholar decreases the odds of experiencing this type of negative collaboration experience by 66.8 percent (exp (B) = 0.332).

To partly address the difference in career length between the cohorts, we also analyzed negative collaboration experiences for the most recent article. These results are presented in Table 9. The results in Table 9 also confirmed our expectations about the respondents' collaboration experiences on their most recent article (i.e., our second hypothesis). We found that for their most recent article the junior cohort was significantly more likely than their senior peers to say that: (1) their contribution was greater than their coauthors and (2) at least one coauthor received credit when s/he did not deserve it.

The regression models in Table 6 allowed us to further test hypothesis 2 for the most recent article, while controlling for gender and coauthor affiliation. In short, Model 1 and Model 2 in Table 6 confirm our expectations for hypothesis 2. The respondents with shorter career ages were more likely to experience the negative collaboration experiences outlined in both models (i.e., feeling their contribution was greater than their coauthors and having at least on person receive coauthor credit without deserving it).

In sum, our regression analyses yield mixed results for our second hypothesis. For the full career of a researcher, we found a significant relationship between career age and likelihood of experiencing a negative collaboration experience for both Models 2 and 4 in Table 8. This means that more junior researchers are more likely to experience: (1) co-authorship credit being denied to a deserving collaborators and (2) a colleague being listed as a coauthor when they did not make a contribution to the research. Yet, junior researchers are not more likely than their senior colleagues to experience: (1) a coauthor not finishing agreed upon activities and (2) a coauthor claiming lead authorship without deserving it. For the most recent article, however, we find that junior researchers are more likely to experience two types of negative collaboration experiences (i.e., feeling their contribution was greater than their coauthors and having at least one person receive coauthor credit without deserving it). These results were presented in Table 6.

Discussion and conclusion

Research limitations

There are several limitations to our study that we need to highlight briefly. First, as mentioned at the end of section "Hypothesis 1: Collaboration Experiences by Coauthor Affiliation", we do not have data that reports the coauthor affiliation for the respondent's full career. Thus, we can only test hypotheses 1a–1c for the most recent article. In future data collection efforts, it will be important to capture coauthor affiliation over a longer time span to further test these hypotheses. Second, we explore the comparison of two cohorts in this study, but unfortunately we are not able to use panel data for this analysis. Instead we use a cross-sectional data collection effort to compare the participants' responses based on their career age. We believe that a panel data collection design would answer some important questions that we bring up in this study. Third, we acknowledge that survey data collection does have weaknesses—just as bibliometric datasets have different weaknesses. There is often strength in combining these two types of datasets. Unfortunately, we were not able to do this for the current study. Yet, we would like to blend survey data collection with bibliometric datasets in the future to get a more detailed picture of the relationship between co-authorship patterns and collaboration experiences. Fourth, the design of our survey data collection means that we have data from individuals reporting their collaborative experiences, not from multiple individuals on the same collaborative teams. Clearly, negative collaboration experiences might look different if we were able to compare the perceptions of all respondents that participated in the collaboration (i.e., all team members). This is a challenging limitation to address in a survey data collection that is as large and dispersed (across disciplines) as ours has been.

Key findings

We believe that our study findings have three important summary points that we will expand upon in this section. First, disciplinary differences in collaboration patterns do exist, but some common trends of research collaboration exist across different disciplines. Our results show that, in line with previous studies, STEM scholars have a higher rate of coauthored papers than social sciences scholars (i.e., represented by economics in our study). Also, mathematicians demonstrate a significantly lower rate of coauthored papers than other STEM colleagues. These disciplinary differences may result from the distinct natures of research activities in different disciplines (e.g., life science and engineering scholars work in a team-based laboratory context, while mathematicians often do their research individually). Our analyses, however, highlight one important dimension of social dynamics of research collaboration—negative collaboration experiences across disciplines. Some factors, such as spatial proximity and cohort differences, are those which negatively influence collaboration experiences across all disciplines in our study. The implication of these results is that contemporary scientific research communities, with collaboration as the norm, face common issues that correlate with negative collaboration experiences even though there are disciplinary differences in collaboration patterns.

Second, although the literature suggests that spatial proximity leads to additional opportunities for communication between collaborators, we found that collaborating with people at the same university does not necessarily lead to fewer negative collaboration experiences. Based on our analyses, collaborating with colleagues in the same university is more likely to lead to negative collaboration experiences (as shown in Tables 5 and 6). Therefore, spatial proximity does not ensure a good and fair collaboration relationship. On the other hand, our analyses demonstrate the cross-sector collaborations (i.e., with private firms) are more likely to result in a negative collaboration experience.

Third, our empirical analysis shows that negative collaboration experiences are an important dimension of scientific collaboration that disproportionately impact younger scholars across all disciplines. Our results show that respondents in the junior cohort are more likely to have some types of negative collaboration experiences, including contribution issues and unequal authorship credit decisions. These results could be explained by the fact that, compared to senior scholars, junior scholars face more pressure in terms of getting tenure, promotion, resources and academic prestige. Junior scholars, who hold relatively less powerful positions in academia, may get opportunities of co-authored articles at the expense of unfair treatment and negative experiences. One important implication from our study is that, rather than taking the cohort difference for granted or simply assuming "it is the way it is," university leaders and department directors need to contemplate this problem and manage to create a friendly and fair collaboration environment for junior and next generation scholars.

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