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Exploring Trade-offs in the Organization of Scientific Work: Collaboration and Scientific Reward

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When do scientists and other innovators organize into collaborative teams, and why do they do so for some projects and not others? At the core of this important organizational choice is, we argue, a trade-off scientists make between the productive efficiency of collaboration and the credit allocation that arises after the completion of collaborative work. In this paper, we explore this trade-off by developing a model to structure our understanding of the factors shaping researcher collaborative choices, in particular the implicit allocation of credit among participants in scientific projects. We then use the annual research activity of 661 faculty scientists at the Massachusetts Institute of Technology over a 31-year period to explore the trade-off between collaboration and reward at the individual faculty level and to infer critical parameters in the collaborative organization of scientific work.

Keywords: science; collaboration; academic science; productivity; scientific credit
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1. Introduction

In 2008, the *Journal of Instrumentation* published a paper entitled "The ATLAS Experiment at the CERN Large Hadron Collider," documenting the installation and expected performance of the ATLAS detector—a critical component of the Large Hadron Collider designed to extend the frontiers of particle physics. As the paper states, "[t]his detector represents the work of a large collaboration of several thousand physicists, engineers, technicians, and students over a period of fifteen years of dedicated design, development, fabrication, and installation" (Aad et al. 2008, p. 1). This crisply illustrates the changing nature of scientific work, with the need for large numbers of individuals with distinctive expertise to work collaboratively in the solution of a complex scientific problem (Jones 2009). However, while the demands for new, more expansive modes of organization push scientists toward larger collaborative groups, the reward system for science has not dramatically changed. Decisions about tenure and promotion depend heavily on public credit given to individual authors of high-impact papers in refereed journals, reflecting the author's novel and singular contributions to a field's knowledge base (see Dasgupta and David 1994).

Traditionally, the first author has been given credit as the main experimenter, and the last author is given credit for oversight or mentoring of the project. The "ATLAS" paper described above, in contrast, has over 1,000 authors listed alphabetically, a situation that nullifies recognition for individual scholarly contributions. As the importance of major collaborations expands, knowledge workers with high levels of organizational autonomy—such as academic scientists, computer programmers and independent inventors—must decide whether to pursue collaborations to achieve scientific goals at the expense of personal credit, or to forgo collaboration and make smaller contributions that are more directly attributable to their efforts. This choice is all the more difficult as knowledge workers increasingly face more autonomy, enabling them to more frequently choose the degree of collaboration they want to pursue.

The trade-off between collaboration and credit is also an issue of managerial import, since supervisors of large teams must decide how to allocate credit and other task-based incentives (Holmstrom 1982, McAfee and McMillan 1991). The collaboration versus credit question is also of considerable theoretical interest to scholars in light of the increased collective organization of knowledge work inside organizations, in the academy and in knowledge communities (Cummings and Kiesler 2007). In other words, the increasing complexity of projects and the resulting demands for greater collaboration raise similar questions about credit versus collaboration in many segments of the world of work, not simply in the halls of academia.

The rise in collective work in general, and collaborative work in particular, suggests that collaboration is a highly advantageous organizational choice (Wuchty et al. 2007). Empirical evidence repeatedly shows that the creative outputs accomplished by a larger number of people tend to be of higher quality, particularly for scientists (Singh and Fleming 2010, Wuchty et al. 2007) but also, for instance, in paintings (Hargadon 2007) and theater (Uzzi and Spiro 2005). These "facts on the ground" are also greeted with great optimism among some scholars, who enthusiastically describe the emergence of a "new norm" of collectiveness replacing the age-old tradition of the individual genius (Johansson 2004, Beaver 2001, Wray 2002). Certainly, many studies highlight collaboration's positive aspects: the ability to tap into diverse sources of knowledge (Fleming et al. 2007), the potential to democratize knowledge production (von Hippel 2005), and greater levels of creativity (Hargadon 2003).

Should we, therefore, assume that collaboration has no disadvantages as a way to organize knowledge work, or are there hidden, unmeasured costs? Scholars in social psychology have provided a more nuanced perspective on the costs of collaboration on creativity (Paulus and Nijstad 2003). Others taking an efficiency perspective note that "a trivial but obvious cost [of collaboration], only one person can talk at a time during meetings—assumedly, such communication is instantaneous and almost costless within an individual" (Singh and Fleming 2010, p. 53). All these analyses, however, explore the trade-offs at the level of a particular project or knowledge output e.g., a paper. They fail to account for the trade-off from the perspective of an individual knowledge worker.

For an individual scientist, the choice of collaboration is made in the shadow of possible trade-offs in credit allocation as well as other efficiency considerations (Engers et al. 1999, Gans and Murray 2013a). However, the current analysis of collaboration ignores whether the benefit to individuals of collectiveness is offset by high potential costs in terms of credit allocation (and other efficiency costs). Importantly, it also ignores the awareness by scientists of this trade-off, as well as the choices they make in light of their consciousness of this trade-off. In other words, it fails to capture the endogeneity of individuals' collaborative choices.

In this paper, we take an individual-level perspective and evaluate the key trade-off between the possible benefits of collaboration for the generation of specific outputs—in terms of quantity and quality—and the costs of collaboration to individuals' overall productivity and credit allocation. Specifically, we develop a theoretical model that focuses on the decision of an individual scientist in managing the collaborative aspects of their portfolio of research activities. Building on elements of Becker and Murphy's (1992) model—which is unrelated to scientific work but highlights production choices—our model makes three assumptions: that a scientist has a fixed time to allocate to all projects, has discretion in the mode of collaboration and third, is motivated not only by maximizing quality (citations) but by maximizing citations allocated to them. These assumptions allow us to derive a set of predictions regarding collaborative behavior and credit allocation trade-offs. We then test these assumptions by examining the academic publications of 661 faculty-scientists from one institution—the Massachusetts Institute of Technology—over a 31-year period from 1976 to 2006.

Our approach is narrower in scope than the massive data-based efforts that analyze millions of knowledge outputs (Newman 2001, Wuchty et al. 2007) but larger than qualitative small-scale investigations (Melin 2000, Hara et al. 2003). Taking an individual-level approach allows us to consider not only the output of collaboration but its *net* value. It presents three crucial advantages over prior studies. First, we can make a realistic examination of the relationship between collaboration and credit at the scientist-year level. Second, we can control for an individual's tendency to consistently take part to larger or smaller projects by adding individual-level fixed effects. Third, we can control for the broader organizational environment by focusing on one institution (adding department-year level fixed effects).

Our empirical results confirm that collaboration (among Massachusetts Institute of Technology (MIT) researchers) is associated with more highly cited work on a per-paper basis, but also with a cost in terms of individual publishing productivity and credit sharing. Our data show that a scientist collaborating with one other person for one year will see his or her fractional publishing productivity fall by over 30%, indicating that the two together publish less than they would if they had worked separately. In addition, scientists cannot claim full credit for collaborative papers. Our results are consistent with scientists receiving around 70% of the total credit for the year's output when collaborating with one other person—therefore suggesting that scientists behave as if they expect to be rewarded disproportionately more for collaborative work than individual work. The relationships are nonlinear, however. Larger collaborations appear less advantageous. Finally, not all types of collaborations are equal. Cross-departmental collaborations tend to produce higher-quality papers at a lower productivity penalty than within-departmental work. Free riding is also apparent: the quality gain is particularly low and the productivity loss is particularly high when collaborating with senior scientists, especially if that scientist is from the same department.

This paper is organized into five sections. In §2 we outline the trade-offs between collaboration as an input into scientific work and credit sharing in the output of collaboration. In §3 we lay out a formal model of this trade-off from which we derive clear hypotheses. In §4 we describe our setting and method. We detail our results in §5 and end with discussion and conclusions.

2. Collaboration vs. Credit Trade-off

Enthusiasm for collaboration is most visible among practitioners: A large number of popular press articles, books, and business consulting reports claim that collaboration provides a superior form of work organization (Hoerr 1989, Dumaine and Gustke 1990, Katzenbach et al. 1993, Orsburn and Moran 2000, Koplowitz et al. 2009). Similarly, in scientific research, the vast majority of policymakers have embraced the trend toward larger research groups and support its further development (Katz and Martin 1997, Landry and Amara 1998, Stokols et al. 2005). In the United States, the National Institutes of Health (NIH) Roadmap has made the promotion of collaborative research one of its priorities (Zerhouni 2003). Accordingly, it has made available a number of grants to support collective science. For example, the aptly named "Glue Grants" program from the National Institute of General Medical Sciences has allocated hundreds of millions of dollars to encourage scientists to collectively tackle "major problems in biomedical research" (Zuckerman and Srivastava 2010, p. v). Overall, the positive perception of collaboration in scientific research was crystallized in the *Science* editorial written by a former National Science Board[1] chairman, arguing that "It is clear that knowledge and distributed intelligence holds immense potential, both from a scientific standpoint and as a driver of progress and opportunity for all Americans" (Zare 1997, p. 1047).

Edward Lawler, in an interview for *Fortune*, took a more nuanced view, in line with our theoretical and empirical approach, when he noted that "teams are the Ferraris of work design, they're high performance but high maintenance and expensive" (Dumaine 1994, p. 2). This highlights the central tension between the positive benefits of collaboration and the possible negative trade-offs for creative work. In laying out the trade-offs, we focus on the benefits of collaboration (versus working alone) from a variety of theoretical perspectives and then contrast this with the costs, including efficiency considerations but also more centrally the costs of credit allocation.

2.1. The Benefits of Collaboration

Researchers, like many practitioners, are traditionally optimistic about the impact of collaboration on creative work. At the core of this perspective lies the notion that the division of labor allows individuals endowed with different knowledge, beliefs, skills, and social networks to come together, thus enabling creativity and novelty. Accordingly, groups establish an ideal context for creativity through the recombination of existing ideas (Gilfillan 1935): the variety of ideas and contexts to which group members have been exposed can be easily united during collaborative work, potentially igniting an explosion of novel ideas—a phenomenon popularized as "the Medici Effect" (Johansson 2004). It has been argued that collaborative groups enhance the circulation of knowledge by bringing together members with different information, social networks, and skills (Cummings 2004, Reagans et al. 2005, Ding et al. 2010). They do so in part because individuals serve as brokers, fostering inspiration across domains (Hargadon and Sutton 1997, Singh and Fleming 2010, Girotra et al. 2010). More specifically, researchers have documented that social interactions can indeed lead to fleeting moments of collective creative insight (Hargadon and Bechky 2006) and that collective work enables members to identify and filter out bad ideas before they fully develop (Singh and Fleming 2010). In addition, groups can be safe arenas for individuals to express original ideas without fearing ridicule (Edmondson 1999). With regard to scientific work, scholars argue that by bringing together individuals endowed with different types of knowledge (Porac et al. 2004, Hara et al. 2003), collaboration allows scientists to take advantage of specialization in the deep stock of scientific knowledge while at the same time gaining the benefits of breadth (Jones 2009).

Empirical evidence supports the view that collaboration leads to significant benefits on a variety of output dimensions: the commercial success of creative work such as comic books, Hollywood productions, and Broadway musicals, as well as its reception by critics, have been linked to collaboration (Taylor and Greve 2006, Cattani and Ferriani 2008, Uzzi and Spiro 2005). Survey data and field work in firms also highlight the positive performance of groups performing creative work when compared to individuals (Obstfeld 2005, Burt 2004, Hargadon and Bechky

[1] Governing body of the National Science Foundation.

2006). As noted in the introduction, more systematic quantitative evidence linking tasks with greater creativity to larger groups rests largely on analyses of two forms of communication of scientific knowledge: patents and papers. Here, the data show that outputs authored by more scientists tend to receive more citations (Adams et al. 2005, Wuchty et al. 2007, Fleming 2007). For instance, Wuchty et al. (2007), studying 20 million scientific publications and over two millions patents, find a clear and increasing advantage of collaborative work across broad research areas. Specifically, science and engineering papers written by two authors received 1.30 more citations than sole-authored papers in the 1950s, and this ratio increased to 1.74 by the 1990s.

Beyond assessing the *average* effect, collaboration is thought to influence the variance in creative outcomes. The direction of this relationship, however, is complex, and current results are contradictory. On one hand, Taylor and Greve (2006) find that collaboration in comic books increases the variance in good and bad outcomes. On the other hand, in analyzing U.S. utility patents, Fleming (2007) finds the opposite—i.e., individual inventors are the source of more failures and more breakthroughs. More recently, a careful study of the creative outcome distribution of over a half million patents (as captured by their citations), using quartile regressions shows that collaboration reduces the probability of poor outcomes while increasing the probability of extremely successful ones (Singh and Fleming 2010).

2.2. Trade-offs—Coordination and Credit

Research (as well as personal experience) suggests a number of potential *coordination costs* associated with collaboration. These costs consume time and have a variety of origins including conflicting goals and incentives, communication difficulties, the need to educate or translate the works of collaborators of different backgrounds, and the requirement for establishing new processes and routines to distribute, synchronize, and monitor the progress of work. Leslie Perlow perhaps most eloquently describes the issue of synchronization in her study of the organization of time at work among software engineers. Using data from a nine-month field study, Perlow (1999) documents how interactive activities can foster insights and learning. More importantly, she shows that these activities exact a high cost in terms of individual productivity when they are not synchronized, leading to “time famines” for knowledge workers. Coordination costs are also documented in academic research; for instance, Porac et al. (2004) found that the most heterogeneous collaboration in their study had the greatest number of issues of communication and synchronization. However, they noted a large increase in productivity after its members had learned to work together. Similarly, Cummings and Kiesler (2007) have found that multiuniversity scientific collaboration imposes considerable coordination costs and leads to underperformance in the absence of a significant coordination effort.

Further drivers of coordination costs have been explored in the social psychology literature, which outlines several cognitive processes leading to inefficiencies in collaboration (Diehl and Stroebe 1987). First, “production blocking” results from the chaotic interactions of the group, which impede the emergence of a consistent train of thoughts. Second, “evaluation apprehension” stems from the fear that some members might have of the others’ judgment of their ideas. Finally, some authors have emphasized “information bias,” which stems from a search for consensus within groups (Paulus 2007). It should be noted that a recent lab study by Girotra et al. (2010) finds that many of these drawbacks of collaboration can be mitigated through hybrid structures, in which individuals first work separately and then work together. Overall, prior research suggests that the coordination difficulties stemming from collaboration in creative work are generally associated with a loss of individual productivity.

Credit allocation is the second major potential constraint or “cost” to collaboration. This arises because credit is central to the reward system in knowledge work, particularly for scientific research conducted in the academy in accordance with the norms of open science (Dasgupta and David 1994). However, although credit can be linked to a particular publication of “piece” of knowledge work, such credit must also be allocated to its producers—the authors. When researchers work and publish alone, they serve as the sole recipients of credit for the quality of the output. In contrast, collaboration requires a more complex allocation calculus. The central importance of this issue for collaboration in creative work arises because, as Merton (1988, p. 621) noted, “[citations] are in truth central to the incentive system and an underlying sense of distributive justice that do much to energize the advancement of knowledge.” Nonetheless, citations counts have been criticized for a number of reasons, including the fact that—independently of the article’s “intrinsic” merits—the amount of citations it is likely to receive will depend on the year of its publication, its field, the journal where it is published, its style, its author, its availability online, etc. (Bornmann and Daniel 2008). Although some have tried to disentangle quality from popularity (Salganik et al. 2006), such distinctions are problematic in creative work, where—as Stein’s definition suggests[2]—broad acceptance by the

[2] Morris Stein famously defined creative work as “a novel work that is accepted as tenable or useful or satisfying by a group in some point in time” (Stein 1953, p. 311).

audience is often considered the only standard upon which quality can be assessed (Stein 1953).

In science, as in other types of creative work, impact is paramount. "For science to be advanced, it is not enough that fruitful ideas be originated or new experiments developed or new problems formulated or new methods instituted. The innovations must be effectively communicated to others. That, after all, is what we mean by a *contribution* to science—something given to the common fund of knowledge" (Merton 1968, p. 59). It is, of course, possible that research developed via collaboration will have a greater impact because a larger team has a superior ability to communicate, mobilize support for, and bring attention to novel ideas. Collaborations play both a social and a cognitive role in this respect. In its social role, a group provides greater communication channels for the dissemination of novel ideas, enabling more visibility through the distinct set of relationships that each group member can use to promote the novel idea (e.g., Allen 1978, Tushman and Katz 1980, Valderas 2007, Ancona and Caldwell 1992, Reagans and Zuckerman 2001) Collaboration can also be instrumental in bringing legitimacy to a novel idea. Merton, for instance, noted that famous researchers lend visibility and credibility to a paper and that therefore students sometimes "feel that to have a better known name on the paper will be of help" (Merton 1968, p. 57), a proposition recently validated in the case of the protocols submitted to the Internet Engineering Task Force (Simcoe and Waguespack 2011). Similarly, in Hollywood, collaboration with individuals who are central to the network of producers can earn legitimacy (Cattani and Ferriani 2008).

Nonetheless, while garnering greater attention overall, each individual contributor to the research must consider how this additional impact will shape his or her own credit allocation—a consideration that has not been heretofore examined. More specifically, researchers must consider the trade-off between the greater impact overall and the credit allocation they receive and how it is spread among numerous authors. As the Hadron Collider paper starkly illustrates, if individual authors receive only fractional credit allocation consistent with a linear function of the number of authors, collaboration becomes a much less appealing prospect (absent other modes of credit for research activities). As an illustration, consider the decision of talented scientists—should they spend a year engaged in two collaborative projects, each with one partner engaging 50% of their time in each project, or should they work alone? That decision is tied to the amount of credit received for collaborative projects compared with other projects. When a scientist devotes time to a collaborative project, he or she must take into account not only the balance of quality versus coordination costs, but also the possibility that she or he receives only fractional attribution for the resulting output. Thus, the collaborative projects that we observe scientists undertaking will likely reflect the highest quality among those projects (an outcome that likely biases current results around the returns to collaboration).

Thus, credit allocation, as well as the norms associated with credit allocation, must be incorporated into current empirical and theoretical perspectives regarding collaborative choices, particularly from an individual perspective. This is challenging because we have relatively little systematic data regarding credit allocation practices. The issue of authorship and credit has received widespread discussion in the scientific press, particularly concerning "ghost" authors who make only limited contributions to a paper. In a recent release, publisher Elsevier noted that "[n]aming authors on a scientific paper ensures that the appropriate individuals get credit, and are accountable, for the research" (Elsevier 2013). Nonetheless, ours is the first paper that incorporates credit allocation as well as coordination into a model of collaboration. It is also the first that attempts to use empirical data to derive a possible credit allocation function from observable collaborative choices of scientists over many years of research activity.

3. Formal Model and Hypotheses

Empirical evaluation of the costs of collaboration is centrally an issue of measurement. While many approaches can measure the quality of research output and the level of collaboration—in the form of citations and formal coauthorship, respectively—these measures do not capture the costs of coordination and credit allocation. If instead we consider a scientist's collaborative choices at the individual level, we can understand the trade-offs they make in coordination and credit.

To shed light on these trade-offs and formulate hypotheses, we have developed a formal model that explicitly considers the drivers of observable variables by formalizing the different underlying models that scientists might use to determine their own portfolio trade-offs. In this section, we provide that model and use it to motivate our empirical approach and the inferences that might be drawn from it. The goal of the model is to clearly exposit the benefits to collaboration and the possible credit allocation costs in a situation where scientific rewards from collaboration are clearly and consistently defined.

To this end, we focus on the decision of an individual scientist in managing a portfolio of activities. This requires several assumptions that, while stylized, are consistent with the evidence of scientists' broader choices and preferences. First, we assume that the scientist has discretion over the set of projects worked on and on the structure of collaboration for any given project. In reality, collaboration is a mutual decision (and an overture to collaboration could be rejected). For simplicity, we assume here that the scientist has full discretion over this choice. (We will comment on the implications of that simplifying assumption below.)

Second, we assume that the scientist is motivated both by maximizing the total number of citations he or she receives for a portfolio of work and for the credit attribution of those citations. Specifically, the scientists are motivated by the citations that are attributed to them rather than those attributed to other collaborators. For instance, if a scientist completes and publishes a single-author paper, she or he receives attribution consisting of the total amount of citations to that paper. However, when the scientist publishes a coauthored paper, that attribution may not be the full amount of citations to that paper. Instead, his or her "share" depends upon a variety of factors. Although there is a paucity of empirical evidence on attribution, a number of factors are likely to intermediate, including the identity of the collaborator (e.g., relative rank, field) and number of collaborators. It should also be noted that, although we use the expression "share of attribution" because this is a useful way of conceptualizing attribution, we do not impose a requirement that the "shares" of all scientists involved in a project add up to one.

Third, we assume that our scientist has a fixed amount of time to allocate across all projects and all the activities that constitute those projects. In reality, a scientist could choose the amount of time to devote to research as opposed to other activities, and this choice may be impacted by collaboration decisions. However, it is simplest to assume that scientists have a fixed allotment of time available for research and that they are maximizing the effective allocation of that time. As a starting point, we build on the model of Becker and Murphy (1992). Their model concerned the division of labor in product activities, and they did not consider either scientific research or scientific collaboration. However, some elements of their model are well matched to the environment under consideration here. Our model differs in the concept of reward attribution and the notion that there exists a portfolio of projects; Becker and Murphy (1992) consider only one project.

3.1. Model Setup and Assumptions

Let us begin with the "production function" for citations from a particular paper. Following Becker and Murphy (1992), we assume that there is a continuum of tasks on the unit interval $s \in [0, 1]$ that must be performed to produce a paper from a research project. To this end, suppose the number of citations for a paper is Q, where

$$Q = \min_{0 \leq s \leq 1} Q(s). \tag{1}$$

The Leontief production function captures the notion that each task, s, must be performed for output to be nonzero. The key assumption here is that tasks are complements. Each task can itself be performed at a certain degree of quality, $Q(s)$, where we assume that $Q(s) = E(N)T^{\theta}(\mathrm{S})$, where E is the productivity associated with total hours, $T(s)$, devoted to task s, $\theta \in (0, 1)$ and N is the total number of collaborators on the project. We assume that $E(1) = 1$ and E is increasing in N. This is a simple way of capturing the notion that specialization increases productivity.[3] However, collaboration also requires time, $c(N)$, to be devoted to coordinating the activities of that team.[4] As outlined above, past studies of collaboration have focused on understanding the net effect of changes in E and c with N. As we demonstrate below, measures of these are complicated by time constraints and the fact that scientists pursue a portfolio of projects with varying levels of collaboration over time.

3.2. Equilibrium Collaboration for a Single Paper

To begin, we focus on the allocation of time for a given paper. Suppose that a scientist, i, is assigned a set, S_i, of the tasks of a paper. Then total time devoted by i to the paper is $T_1 = c(N) + \int_{s \in S_i} T(s)\, ds$. We assume here that the opportunity cost of that time is $C_i(T_i)$, a function modeled explicitly below. Given this, i solves the following problem:

$$\max_{\{T_i(s)\}_{s \in S_i}} \alpha(N)Q - C_i(T_i), \tag{2}$$

where $\alpha(N) \leq 1$ is the fraction of total citations from the paper attributable to i. That is, the scientist chooses time allocated to a project that maximizes their share of the expected quality of the project less the opportunity cost of that time. We assume that if $N = 1$, then $\alpha = 1$. This fraction is considered to be independent of Q realized.[5]

[3] Becker and Murphy (1992) assume that productivity increases also require an allocation of time, but ultimately this reduces to specialization increasing productivity. For notational simplicity, we remove that extraneous layer of endogeneity here.

[4] Becker and Murphy (1992) did not model coordination costs specifically and assumed that those costs were a function $C(N)$. Here we provide an additional layer of endogeneity consistent with our notion that scientists are allocating time across projects and thus, time spent in coordinating activities as an opportunity cost determined by time not allocated to other projects.

[5] One can imagine that the attribution may come from market assessments as to the relative contribution of collaborators in a scientific team and such attribution may itself depend on the performance of tasks the scientist is known for. Thus, the fraction of total

To derive the chosen allocation of time, as tasks are symmetric, we assume that time devoted to each task is equal. Thus, $\int_{s\in S_i} T(s)\,ds = S_i T(s)$ and $Q(s) = E(N)T^{\theta}(s)$ so the optimal $Q(s)$ satisfies the minimum of this or the minimal quality achieved for a task by collaborating scientists.

To complete the model, assume that if there are N collaborators to a project, they split the number of tasks between them equally. This is a natural assumption if scientists are symmetric[6] and results in $Q = E(N)T(s)^{\theta}$. Holding the time allocation choices of other collaborators as given, the scientist chooses T_i to maximize

$$\max_{T_i} \alpha(N)E(N)(N(T_i - c(N)))^{\theta} - C(T_i). \tag{3}$$

Note that if $\min_{j\neq i} T_j < T_i$, it is optimal to lower T_i to that minimum. Thus, there is potentially a continuum of equilibria in this game. The equilibrium with the highest allocation of time, T_i^*, is characterized by the first-order condition

$$\alpha(N)E(N)N\theta(N(T_i - c(N)))^{\theta-1} = C'(T_i^*). \tag{4}$$

This shows that in choosing the allocation of time to a project, the scientist considers the opportunity cost of that time (to be modeled explicitly below) and the impact of time on their share of paper quality net of time required to coordinate a collaborative endeavor. This equation plays a key role in what follows.[7] Specifically, we focus on the equilibrium with the highest allocation of time.

3.3. Equilibrium Collaboration with Multiple Papers

Our purpose is to measure the impact of collaboration on productivity and make inferences about the benefits and costs of collaboration, as well as the structure of the scientific reward function for research teams. The above analysis shows that collaboration can be beneficial because of the exploitation of specialization and the division of labor, but it potentially incurs a cost in coordination. However, collaboration also affects the time available for a scientist to pursue other papers, particularly sole-authored projects without collaboration. Here we introduce that option into the model.

In moving to consider a scientist's portfolio of papers, our model exposes the central issue that must be considered when studying the impact of collaboration on scientific productivity and quality: the limitations of studies that focus purely on collaboration versus noncollaboration without accounting for time considerations or individual scientist effects. Because individual scientists are time-constrained, collaborative projects affect the amount of attention that can be devoted to other projects. Scientists must therefore consider the relative advantage of pursuing higher-quality collaborative projects against single-authored projects when choosing how to allocate their time.

Here we examine the impact for a scientist of introducing collaborators on a project and its effect on another project where the paper resulting from the solo project is single authored. We assume that the scientist can only work on one noncollaborative project at a time. Under this scenario, there are no advantages from the division of labor and the scientist faces no coordination costs and receives attribution equal to the full value (in terms of quality or citations) of the paper. We otherwise assume that the paper's production function is equivalent to that specified above.

For the single-authored paper in the portfolio, if we assume that the total time allocation a scientist has is 1, then

$$C'(T_i) = \theta(1 - T_i)^{\theta-1} \tag{5}$$

Using this we can solve for the optimal time allocation to the collaborative project given N:

$$\begin{aligned}
&\alpha(N)E(N)N\theta(N(T_n - c(N)))^{\theta-1} = \theta(1-T_i)^{\theta-1}\\
&\Rightarrow\quad T_i^* = c(N) + \frac{1-c(N)}{1+N(\alpha(N)E(N)N)^{1/(\theta-1)}}\\
&\Rightarrow\quad 1-T_i^* = (1-c(N))\frac{N(\alpha(N)E(N)N)^{1/(\theta-1)}}{1+N(\alpha(N)E(N)N)^{1/(\theta-1)}}.
\end{aligned} \tag{6}$$

Given this, scientists face a choice. They can collaborate on one of the papers with N participants (leaving a second paper single authored) or they can pursue two single-authored papers. The choice depends not only on the quality improvement (if any) arising from collaboration but also from the time cost (if any) diverted from single-authored papers as well as the level of attribution the scientist expects from the collaborative project.

How does an increase in N impact upon the time allocation, T_i^*, to the collaborative project compared with the single-authored project? From (6) note that T_i^* is decreasing in $N(\alpha(N)E(N)N)^{1/\theta-1}$, a summary statistic reflecting the marginal return to time invested

citations attributable to i may be dependent upon the realized quality of a project. Thus, for a given scientist, $\alpha(N)$ could vary over time, with who their collaborators are and with their stage of career or notoriety. We assumed away these complexities here. Gans and Murray (2013b) investigate it in more detail with a formal model.

[6] This is a strong simplifying assumption as it assumes that no regard to differences in the opportunity cost in time are taken into account when allocating tasks between collaborating scientists. However, the qualitative predictions of the model that we focus on for this paper would not be changed if this assumption were relaxed.

[7] It could also be used to analyze other issues such as the optimal team size. These are issues explored in Haeussler et al. (2014).

in single-authored relative to collaborative projects independent of coordination costs. This marginal return varies with N in the following manner:

$$\begin{aligned}\frac{\partial(N(\alpha(N)E(N)N)^{1/(\theta-1)})}{\partial N} &= (\alpha(N)E(N)N)^{1/(\theta-1)} \\ &\quad + \frac{N}{\theta-1}(\alpha(N)E(N)N)^{(2-\theta)/(\theta-1)} \\ &\quad \cdot \left(\frac{\partial\alpha}{\partial N}E(N)N + \frac{\partial E}{\partial N}\alpha(N)N + \alpha(N)E(N)\right).\end{aligned}$$

This expression is positive if $\alpha(N)E(N)$, i.e., productivity and attribution, does not vary much with N. In this situation, an increase in collaboration may allow the scientist to *reduce* the time allocated to the collaborative paper in favor of the noncollaborative paper; consequently, studies focused on collaboration may understate the productivity of collaboration. Alternatively, in cases when the impact of collaboration on productivity is high (i.e., $E(N)$ varies substantially with N) time will be *drawn toward* the collaborative project and away from the single-authored paper, overstating the pure productivity of collaboration. Only by controlling for scientist fixed effects can these distortions be mitigated. A similar issue arises with respect to coordination costs from collaboration: these result in a reduction in "research time" for both the collaborative and single- authored project. Again, to properly identify the portfolio effects of collaboration, we need to consider variations in portfolio mix over time.

3.4. Hypotheses

Our model is deterministic in the sense that the opportunity set of papers the scientist has available is known and does not vary. In reality, at different times, that opportunity set will differ. If we make a simple assumption that movements in the opportunity set over time are independent—that is, not related to multiyear grants, administrative duties and new collaborative teams—then we can use the model to construct hypotheses based on our observations of the year-to-year quality of a given scientist's portfolio. Three hypotheses can be tested, the first being the average quality of publications.

Hypothesis 1 (H1). *Scientists have higher-quality average publications in years when they collaborate more.*

This is a direct implication of the notion that scientists make conscious decisions about collaboration. As collaborative publications involve a fractional allocation of credit, i.e., $\alpha(N) < 1$, and partially unobserved, coordination costs, a scientist will choose a collaborative project only if it improves the quality of his or her portfolio of projects, as measured by resulting papers.

Second, an assumption underpinning our model is that scientists are time constrained. Specifically, we assume that when the scientist single authors all papers, he or she has an output of two papers, whereas if he or she collaborates on one of those papers, the fractional output is $1+\alpha(N)$ or $1+1/N$ in the case of simple fractional allocation. This core assumption can be tested directly by examining the following hypothesis:

Hypothesis 2 (H2). *In years when scientists collaborate more, fractional publications fall.*

Importantly, the model demonstrates that there are conditions under which this hypothesis will not hold as it endogenizes time allocation to papers. Specifically, collaboration may "free up" a scientist's time, allowing more single-authored projects or alternative collaborations to be pursued. This will indicate that $\alpha(N)E(N)N$ does not vary much with N, so T_i^* will fall with N. Thus, the model tells us that rejection of H2 could indicate that either credit does not fall much with N or there are few gains to specialization within collaborations.

Third, suppose collaborative opportunities are equal or harder to come by than individual research projects in a scientist's opportunity set. Then the "rate of return" for collaboration in a particular year should be (weakly) positive.

Hypothesis 3 (H3). *For a given $\alpha(N)$, the fractional quality of the portfolio attributed to scientists in years of increased collaboration should be no less than the quality of the portfolio they achieve in years when they collaborate less.*

The intuition here is that scientists take their expected attribution from collaboration as given and choose their portfolios to maximize their attributed quality. Thus, for a posited $\alpha(N)$ if we see a negative return, this is evidence that the posited $\alpha(N)$ is not consistent with observed collaborative behavior. It is important to note that this latter test is dependent upon key assumptions we have made in the model thus far, including (a) that scientists choose projects to maximize their total attributable citations; and (b) that $\alpha(N)$ is stable over time and across scientists. Below, we explore ways of relaxing these assumptions. Overall, we believe our tests of H3 provide an interesting picture that can be interpreted in light of the theory posited here. The model tells us that examining the returns to collaboration for a given scientist over time will give us an *indication* as to the allocation of attribution in collaborative scientific projects the scientist expects to arise in his academic community.

4. The Empirical Approach

4.1. Data and Setting

Given the challenges associated with our empirical analysis, we have chosen to focus on the collaborative choices and publication outcomes of a sample of scientists over a long period of time, thus allowing us to include both individual and annual fixed effects in our analysis. This contrasts with approaches that compare outputs at the publication level.

Our setting is a comprehensive data set of research publication activity at a single university—the Massachusetts Institute of Technology—including the research output over the 31-year period of 1976–2006, covering more than 650 faculty members in seven departments from the Schools of Science and the School of Engineering. This focus on a *single* university over time is particularly appealing for several reasons. First, a scientist's choice of whether or not to collaborate is little constrained by formal organizational structure. Second, these choices can easily be traced out from one year to the next by following authorship on publications. Third, "quality" can be analyzed using the (albeit imperfect) metric of citations. Fourth, as noted above, our setting offers the opportunity to control for individual effects, allowing us to tease out the impact of collaboration (Woodman et al. 1993). Fifth, by selecting one institution, we can control for institutional setting. Our choice of MIT is not merely one of convenience: it has been shown that prestigious institutions participate more fully in collaborative science (Adams et al. 2005, Jones et al. 2008). Thus, using MIT allows us to examine the "leading edge" of collaboration.

The core of the study is a sample of publishing faculty members drawn from the annual lists as faculty members at MIT (in the Academic Bulletin). Criteria for inclusion are the following. First, we include faculty from the following seven departments: Electrical Engineering and Computer Science, Chemical Engineering, Material Science and Engineering, Mechanical Engineering, Biology, Chemistry, and Physics. These were selected because they include science and engineering disciplines. Second, faculty must be listed for at least three consecutive years to avoid counting visiting professors, whose participation in research groups of particular size might be systematically biased by their short stays. Third, we chose the period from 1976 to 2006 because of ISI data limitations and because 1975 was the year in which the departmental arrangements that remain were established.[8] Fourth, we excluded all the scientists who ever took part in projects with more than 20 authors, due to the decoupling of authorship and contribution for specific projects and particular fields (Knorr-Cetina 1999): using ISI subfields, this removed five "Big Science" subfields: Astronomy and Astrophysics, Multidisciplinary Physics, Nuclear Physics, Instruments and Instrumentation, Particles and Fields Physics. (Note, however, that our results are robust to the inclusion of these scientists in our data.)

We identified 846 individual scientists given our departmental and year criteria. We then excluded 128 (most of whom were professors emeriti in 1976) because of a lack of any publication record for that time period. We further excluded 57 scientists who had taken part in projects that included more than 20 authors. We used our list of 661 publishing faculty as the basis of our analysis. For these people, we collected individual information, including Ph.D. year and topic, from the UMI Proquest Dissertation Database, as well as departmental affiliation and seniority from the MIT course catalogue for 31 years (assistant, associate, full professor, or emeritus). We collected all the articles written by our scientists during their time at MIT using ISI Web of Science. Between 1976 and 2006, the 661 scientists were at MIT for 5,964 faculty-years and wrote 21,054 publications.

4.2. Dependent Variables

Quality: We measure quality (Q in our formal model) by observing the average number of citations received by a scientist for all the papers she or he published in a given year. As noted above, although citation giving is a part of normal science, citation counts are an imperfect measure of quality, impact, or credit. However, across a sample of publications, citations are a relatively objective and convenient measure of an article's quality and impact and have therefore been widely used in science evaluation (Furman and Stern 2011, Leahey 2007, Wuchty et al. 2007). Practically, we used the number of citations received by 2008 (*Cites*) as a measure of impact at the paper level. Using this metric, we can calculate the yearly quality of the scientist's publications by observing the average number of citations received. For scientist i in year t, publication quality was measured as the average count of citations ($Cites_k$) received by each publication k of that year: $Cites_{it} = E(Cites_k)_{it}$.

To examine whether variation in marketing capability (including self-citations) is driving our results about quality, we checked the robustness of all our results using another proxy for work quality: the average journal impact factor (2009 data) of every scientist-year. We could not find a JIF for 16.2% of the publications—the discrepancy coming from low-ranking journals, conference proceedings, journals that have disappeared, and those that have changed

[8] In 1975 the department of Electrical Engineering expanded to become Electrical Engineering and Computer Science and the department of Metallurgy and Materials Sciences merged into Materials Science and Engineering.

names. Each model using JIF was run twice: first by imputing the missing data using the article number of citations (results presented below), and then a second time considering that the missing JIF was 0. These methods led to very similar results.

Productivity (*Quantity*): We measure $NPubs_{it}$, the productivity of a scientist's work (E in our formal model), by keeping the input constant (a scientist-year) and observing the number of papers published in a given year. It is worth remembering that publication data are only a proxy for the number of projects that a scientist is involved with; publications are only the disclosed final outcomes of projects and may therefore undercount the total number of projects if some lead to no publications. Nonetheless, our ability to aggregate publications to the individual faculty-year level serves as an important step toward accounting for inputs into collaboration (Girotra et al. 2010, p. 593). Beyond simply capturing *NPubs*, our approach builds on Lee and Bozeman (2005) and also examines the "fractional count" of paper published. As the simplest functional form of fractional counting of productivity, we compute *Frac_Pubs* the sum of "papers shares" directly attributed to the scientist. In other words, if the scientist i in the year t has published n papers, each of which includes a number $NAuthors_k$ of authors, their fractional publication count for that year is

$$Frac\_Pubs_{it} = \sum_{k=1}^{n} \alpha(NAuthors_k), \quad \text{where } n = NPubs_{it}.$$

Credit Allocation: As detailed in our formal model, we consider scientists' motivation to collaborate as dependent on $\alpha(N)$, the share of their research output that is attributed to them (rather than to their collaborators). For scientists considering collaboration, $\alpha(N)$ captures the cost they will incur from having to share the credit with their coauthors. The specific functional form of this attribution is an empirical question that we examine in this paper. For a given $\alpha(N)$, we compute the number of yearly citations attributed to a scientist's work by summing the citations attributed to the author for every paper of the year. In other words, if the scientist i in the year t has published n papers (k), each of which includes $NAuthors_k$ and has received $Cites_k$ by 2008, the attributed citation count for that year is

$$Att\_Cites_{it} = \sum_{k=1}^{n} Cites_k * \alpha(NAuthors_k), \quad \text{where } n = NPubs_{it}.$$

At one extreme, if $\alpha(N) = 1$, then the credit for a collaborative paper is not split. The cost of collaboration in terms of credit sharing is null, and each author claims the entire credit for each coauthored paper and its citations. At the other extreme, if $\alpha(N) = 1/N$, then the scientists split the credit across every author, and the sum of shares of all scientists involved in a project sums to one. A third possible form is that scientists can claim less credit for a coauthored than for a sole-authored paper, but that the sum of the shares of credit attributed to all the scientists in a coauthored paper is superior to one.[9] We explore this possibility by studying $\alpha(N) = 1/\sqrt{N}$. For the entire sample, we also attempt to assess more precisely the credit allocation function by exploring different values of $b \in [0, 1]$ for $\alpha(N) = N^{-b}$. This latter exercise will provide insights on the range of potential $\alpha(N)$ that are consistent with the collaboration choices that scientists make in our data. In other words, we will use scientists' collaboration choices to infer the cost that they pay from having to share credit with their collaborators.

4.3. Independent Variable—*Collaboration*

We measured the extent of collaboration during a scientist-year by considering the mean number of coauthors (N in the formal model) for all the publications of that year (Wuchty et al. 2007, Adams et al. 2005, Jones et al. 2008). We obtained the number of coauthors on a project ($NAuthors_k$) by counting the number of names in the author field of each of our publications (also referred to as the coauthorship index; Bordons et al. 1996). While coauthorship remains a form of currency in the cycles of scientific credit (Latour and Woolgar 1986), it reflects actual collaboration only to the extent that authorship reflects participation. A few studies have noted that this measure is an imperfect one (Katz and Martin 1997, Cronin et al. 2004). Distinguished researchers are sometimes added to the authorship list despite the fact that their contribution is relatively minor, a practice known as "guest authorship." Conversely, "ghost authors" are individuals who are not recognized as coauthors despite their significant contribution. Recent work has shown that norms of inclusion vary by discipline and that inclusion is often positively correlated to a scientist's social standing (Biagioli 2002, Haeussler and Sauermann 2013, Lissoni et al. 2013). Decoupling contribution and authorship increases measurement error in our analysis: to avoid some of these issues we exclude from

[9] Other synthetic measures of performance have been suggested, such as the index h, which measures for each individual scientist the number of papers with citation superior or equal to h (Hirsch 2005). According to this measure, a scientist would have an h-index of 20 if he or she has published 20 papers having received more than 20 citations and all the other published papers have received fewer than 20 citations. While this measure is attractive because of its simplicity and ability to synthesize quantity and quality at the level of the individual, this measure is not adapted to measuring within-individual variation in performance over time.

our sample scientists who have taken part in any publication with more than 20 coauthors. In our regressions, we also controlled for disciplinary, temporal, individual, and career-related patterns. For scientist i in year t, collaboration was measured as the average number of authors $NAuthors_k$ in that year publications: $NAuthors_{it} = E(NAuthors_k)_{it}$.

4.4. Control Variables

Individual Ability: Individual aptitudes are widely believed to be a predictor of creativity and quality (Amabile et al. 1996, Woodman et al. 1993). Prior research has also shown that better scientists tend to work in larger groups (Zuckerman and Merton 1972). Controlling for individual-level variance in creative ability is therefore crucial if we are to disentangle the impact of collaboration on the quality of scientific work. An important advantage of our setting is that we have a number of observations per individual and can therefore introduce into our models a dummy variable for each of our scientists.

Career Stage: Scientific creativity and propensity to collaborate are widely believed to vary over their career span (Zuckerman and Merton 1972, Jones 2009). It is therefore important to control for such career-level variation. To do so, we introduce an indicator variable for each of the scientist's career stages: assistant professor, associate professor, professor, and professor emeritus.

Department-Year: General citation patterns vary from one year to the next and are known to be increasing over time due to the fast expansion of knowledge production (Cawkell 1976). Moreover, this expansion might vary from one discipline to the next. To control for such variation, we included an indicator variable for all department-years in the sample.

Authoring Position:[10] To check the robustness of our findings and control for authoring position, we introduce a dummy variable when the focal scientist is the first (last) author. At the level of the faculty-year, our *First Author* variable (*Last Author* variable) is the propensity of scientists to be first (last) authors for all of their year's publications.

4.5. A Note on Our Approach

Before we move to describing how we test our hypotheses, we would like to be explicit about what our regressions do and do not accomplish.

Instead of considering collaboration as a treatment, this paper examines collaboration as a choice. This focus on choice provides insights about important issues facing autonomous workers, such as time investment and credit allocation. However, studying collaboration as a choice empirically is also difficult because many of the variables that drive workers' decisions cannot be measured directly in archival data. Because of these measurement issues, we have proposed a formal model of individuals' collaboration choice. This model clarifies our argument about the "data production function" and allows us to study the trade-offs associated with collaboration in a situation where output quality, time investment, and credit allocation are clearly and consistently defined. In other words, our empirical analysis examines individuals' choices that result from a decision process that we model but do not observe.

We are building on prior empirical studies that have uncovered a strikingly persistent pattern: collaboration is associated with creative output of higher quality (e.g., Adams et al. 2005, Jones et al. 2008, Singh and Fleming 2010). Although output quality is a readily observable variable in the form of publication or patent citations, for instance, we argue that other, less easily observable variables might nevertheless constitute essential aspects of collaboration as it is experienced "on the ground." In particular, we argue that two costs of collaborations are unobservable using traditional approaches but are nonetheless significant for creative workers: (a) collaboration requires an investment in time, and (b) collaboration requires sharing credit among collaborators. The omission of these difficult-to-observe costs would lead to overly optimistic conclusions about the relationship between collaboration and creative performance. Yet, these variables are not directly observable to the empiricist. Our formal model clarifies the relationship between these variables and the more traditional variable of output quality. Our empirical analysis of H1 and H2 uncovers new correlations that support our argument that collaboration entails important trade-offs. H3 uses a slightly different approach since we use the hypothesis generated by our formal model to estimate the type of credit allocation functions (i.e., cost from credit sharing) that would be consistent with the collaborative choices that we observe.

We observe year-to-year variation in scientists' propensity to collaborate. This variation might stem from a number of factors driving the scientist's opportunity landscape or from the costs that he or she faces. First, new discoveries and inventions might create novel opportunities for collaboration. As an example, the hack of Microsoft Kinect opened the door to new projects bringing motion-sensing specialists together with specialists from other disciplines (Teodoridis 2014). Second, for individual scientists, the set of available potential collaborators is likely to be shaped by retirements, researchers' mobility, and serendipitous meetings during annual conferences.

[10] An analysis of the impact of authoring position was completed and the paper's results remained essentially unchanged. The analysis was eventually left out of the paper because of space constraints.

Indeed, the random collocation and face-to-face interactions of biomedical researchers have been found to increase significantly the likelihood that they collaborate (Boudreau et al. 2014). Third, collaboration opportunities are likely to be influenced by multiyear grant cycles and administrative duties. Our understanding is that most disciplines in the sample have key annual conference deadlines that motivate project selection and also, in some cases, the generation of new project ideas. In addition, appointments to key administrative posts—both within MIT and external to it—operate on a year-based time frame. For all these reasons, the opportunity cost of collaborative projects is likely to vary across disciplines and over time. We use fixed department-year effects to potentially account for these, even though our theoretical framework would offer no clear prediction as to the direction of bias (if any).

In short, our strategy was not to precisely identify the marginal impact of collaboration. Collaboration is neither exogenous nor random in our data; it is a choice. We observe correlations between collaboration on one hand and paper quality and quantity on the other. We interpret these empirical patterns in light of our formal model of scientists' choice, which also allows us to explore credit allocation. Thus, our goal is to articulate some of the key benefits and costs of collaboration for autonomous creative workers, and we examine these both formally and empirically.

4.6. Empirical Analysis

We study scientist i's decision to collaborate more or less each year t and observe how this decision correlates with the quality and quantity of the papers k that he or she publishes that year. In addition, we estimate the amount of credit that will be attributed to the scientist.

We test H1 (that scientists have higher-quality average publications in years they collaborate more) by assessing the correlation between an individual's annual collaborative behavior and the average quality of the scientist's publications. The mean number of coauthors for the year proxies for collaboration and $(Cites_k)_{it}$ is our measure of quality (we also measure the average journal impact factor as an alternative measure of quality). Because we can control for individual and contextual characteristics, we are building on and bringing further robustness to prior results, suggesting that collaboration is associated with higher quality output (Adams et al. 2005, Wuchty et al. 2007). We use an ordinary least squares (OLS) regression with department-year, individual scientist, and career-stage fixed effects. In all our regressions, robust standard errors are clustered at the level of the individual scientist to account for the nonindependence of observations from the same author. We estimate

$$\ln(1+Cites_{it}) = \beta_0 + \beta_1 NAuthors_{it} + \mu_i + \beta_2 \bar{X}_{it} + \varepsilon_{it},$$

where $NAuthors_{it}$, our key explanatory variable, is the average collaboration of scientist i in year t, and μ_i is the fixed effect for each scientist i; $\bar{X}_{it}$ is a vector of variables controlling individual-year characteristics such as the scientist's average authoring position but including also indicator variables for each department-year and career-stage, and β_2 is, therefore, a vector of parameters.

We test H2 (that scientists' fractional publications fall in years when they collaborate more) by studying the impact of an individual's yearly collaborative behavior on the quantity of the scientist's publications. We thus examine productivity by studying the relationship between collaboration and the number of papers published that year using the *Frac_Pubs* measure to account for the fractional number of publication (and compared to the total number of publication *NPubs*). Because the number of attributed publications per year is a continuous variable skewed to the right, we used the natural log and used OLS with robust standard errors for our estimation. As earlier, we used scientist, career-stage, and department-year fixed effects. Using the same notations as the previous equation, we estimate

$$\ln(1+Frac\_Pubs_{it}) = \beta_0 + \beta_1 NAuthors_{it} + \mu_i + \beta_{2\circ}\bar{X}_{it} + \varepsilon_{it}.$$

As is apparent from our formal model, the benefit of collaboration relative to noncollaboration depends on $\alpha(N)$ the share of the credit attributed to the scientist for a collaborative paper. If scientists behave rationally and maximize their attributed citations, we should find that the hypothesized positive impact of collaboration on quality and its negative impact on quantity would cancel one another. Assuming that collaborative opportunities are scarcer than noncollaborative ones (since collaborators might be hard to find), we might expect that scientists systematically undercollaborate and, therefore, find that the overall returns to collaboration might appear positive. We test H3 (that for a given $\alpha(n)$, the fractional quality of the portfolio attributed to scientists in years of increased collaboration should be no less than the quality of the portfolio they achieve in years when they collaborate less) by examining attributed citations as a function of collaboration for a given $\alpha(N)$. As earlier, we take the natural log of the fractional number of citations and use an OLS estimator with robust standard errors, as well as scientist, career-stage, and department-year fixed effects:

$$\ln(1+Att\_Cites_{it}) = \beta_0 + \beta_1 NAuthors_{it} + \mu_i + \beta_{2\circ}\bar{X}_{it} + \varepsilon_{it}.$$

According to H3, one would not expect that the overall returns to collaboration be negative. Assuming that scientists optimize the citations that are attributed to them every year and $\alpha(N)$ is stable over time and across scientists, for a given $\alpha(N)$, finding negative returns to collaboration would indicate that in our chosen $\alpha(N)$ probably underestimates the actual credit that scientists are getting for the work that they produce. While testing H3, we will consider various different functions for $\alpha(N)$ as described above.

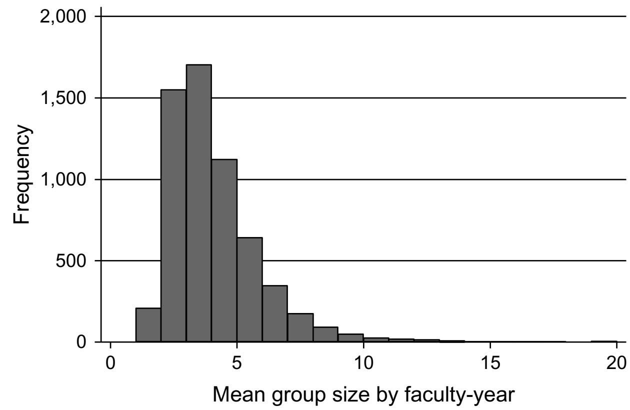
Finally, we deepened our understanding of the mechanisms at work shaping the impact of collaboration on quality and productivity by distinguishing the effect of *different* types of coauthorship. Specifically, we compared the impact on the focal scientist of collaborations with a more junior scientist, a more senior scientist, and a scientist of the same rank. We can also explore the impact of collaborating across departments and/or with non-PIs (principal investigators). To do so, we limited our analysis to the subset of the sample of scientist-years in which every published paper involved only MIT-affiliated authors (2,273 faculty-years and 4,617 publications), allowing us to identify all the MIT PIs, their departments, and their career stages as well as count the number of non-PIs on each paper.

5. Results

5.1. Descriptive Statistics

Tables 1 and 2 present the main variables of our analysis. Over the 5,964 faculty-year observations we have data on a total of 21,054 publications. This allowed us to track the extent to which the researcher collaborated by observing the average number of coauthors for the year. Mean group size (*NAuthors*) is 3.8 authors. Collaboration at the faculty-year level varies between 1 and 20. Scientists did not collaborate at all during only 157 faculty-years (2.6%). In 64% of the faculty-years, average group size was between two and four authors. The entire distribution of group sizes in the data is plotted in Figure 1.

Figure 1 **Distribution of Group Sizes by Faculty-Years (Descriptive Statistics)**



The key dependent variables in our data are quality (average number of forward citations received by the papers produced in a faculty-year), productivity (quantity of papers attributed to the scientist per year), and the overall credit (citations) attributed to the scientist for a year of work. With regard to quality (*Cites*), the average number of forward citations received (by 2008) by the papers written in a faculty-year is 41.3. Turning to productivity, the MIT researchers published an average of 3.5 papers per year (i.e., *NPubs* is 3.5). However, *Frac_Pubs* (i.e., assuming $\alpha(N) = 1/N$) is only 1.1. Both quality and productivity are highly skewed across faculty-years. We also measured the credit attributed to the scientist of the year of work using primarily the three proposed functional forms:

- If $\alpha(N) = 1$, then mean *Att_Cites* is 165.1 citations.
- If $\alpha(N) = 1/\sqrt{N}$, then mean *Att_Cites* is 86.4 citations.
- If $\alpha(N) = 1/N$, then mean *Att_Cites* is 48.7 citations.

Table 1 **Descriptive Statistics at the Individual-Year and Publication Levels**

	Publication level ($n = 21{,}054$)				Individual-year level ($n = 5{,}964$)			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Average group size (*NAuthors*)	4.08	2.26	1	20	3.83	1.87	1	20
Average forward citations (*Cites*)	46.76	111.88	0	4810	41.28	86.89	0	2,595
Productivity—$\alpha(N) = 1$ (*NPubs*)	n.a.	n.a.	n.a.	n.a.	3.53	3.70	1	47
Productivity—$\alpha(N) = 1/N$ (*Frac_Pubs*)	n.a.	n.a.	n.a.	n.a.	1.13	1.11	0.05	9.70
Att_Cites—$\alpha(N) = 1$	46.76	111.88	0	4,810	165.08	388.78	0	8,852
Att_Cites—$\alpha(N) = 1/\sqrt{N}$	24.48	67.21	0	4,810	86.42	211.72	0	4,946.79
Att_Cites—$\alpha(N) = 1/N$	13.80	50.95	0	4,810	48.70	135.39	0	4,819
N_Highly cited publications	0.05	0.22	0	1	0.18	0.53	0	8
Frac_Highly cited publications	0.01	0.07	0	1	0.05	0.17	0	2
Average JIF missing values imputed	4.86	5.57	0	52.59	4.46	4.62	0.02	29.89
Last authored paper	0.63	0.48	0	1	0.61	0.39	0	1
First authored paper	0.08	0.27	0	1	0.12	0.29	0	1
Year	1994.97	8.56	1976	2006	1993.15	8.84	1976	2006

Table 2 **Correlation Table, Main Variables, Individual-Year Level** ($n = 5{,}964$)

	1	2	3	4	5	6	7	8
1 *NAuthors* (*mean group size*)	1							
2 *Cites (average forward cites)*	0.0944*	1						
3 *NPubs*	0.1254*	0.0602*	1					
4 *Frac_Pubs*—$\alpha(N) = 1/N$	−0.1414*	0.0415	0.9026*	1				
5 *Att_Cites*—$\alpha(N) = 1$	0.1068*	0.6097*	0.5092*	0.4712*	1			
6 *Att_Cites*—$\alpha(N) = 1/\sqrt{N}$	0.0414	0.6210*	0.4742*	0.4786*	0.9711*	1		
7 *Att_Cites*—$\alpha(N) = 1/N$	−0.011	0.6095*	0.4022*	0.4415*	0.8794*	0.9655*	1	
8 *Year*	0.2301*	−0.1416*	0.1967*	0.1149*	−0.0520*	−0.0742*	−0.0848*	1

*$p < 0.001$.

Table 2 presents the correlation coefficients of our main variables. Average group size and year are positively correlated (+0.23), i.e., collaboration in our sample has evolved over time toward larger groups. Productivity has also been increasing, and this holds across both *NPubs* and *Frac_Pubs* (0.20 and 0.11, respectively). Consistent with the prior literature, we found a positive correlation between collaboration (*NAuthors*) and quality (*Cites*) (+0.09).The correlation between collaboration and yearly productivity depends on whether we consider *NPubs* or *Frac_Pubs*: For $\alpha(N) = 1$, collaboration is positively correlated with productivity (+0.13) i.e., not surprisingly, on average, collaboration is associated with more authored papers but the correlation is negative for *Frac_Pubs* (−0.14). With regard to credit attribution, for $\alpha(N) = 1$ the correlation is positive (+0.11), but for $\alpha(N) = 1/N$ the correlation is almost null (−0.01). Interestingly, the correlation between productivity and quality appears overall positive, i.e., we do not find evidence of any intrinsic quality–quantity trade-off in academic research.

5.2. Econometric Analysis of Hypotheses

Our H1, H2, and H3 are tested in Table 3. Model (3-1) confirms H1 and in doing so, adds robustness to the result of prior studies in showing that more collaborative output is *on average* of higher quality, even after accounting for individual scientists' propensity to collaborate. The highly significant positive coefficient on group size confirms our H1. More specifically, the coefficient of 0.099 can be interpreted as an increase by about 10% of the average number of citations received per paper for years in which the scientist collaborates with one more collaborator.

Our second hypothesis that collaboration is associated with a loss in productivity was tested in models (3-2) and (3-3). At the level of the year at work, we found that the choice to collaborate in larger groups is not associated with a higher number of authored publications per year (3-2). This result is particularly interesting, since we have seen in Table 2 that the two variables are overall positively correlated in the data. On average, however, it seems that at the level of the scientist's yearly choice, the potential productivity gains stemming from specialization and division of labor are counterbalanced by the costs of coordination. This result is even more striking if we consider that, by choosing collaboration, scientists cannot really be "allocated" all the resulting publications but rather might consider their fractional contribution to the stock of published knowledge i.e., $\alpha(N) < 1$. Our

Table 3 **The Effect of Collaboration Choice on Quality, Quantity, and Credit**

	Quality	Quantity		Credit		
	DV = log(1 + *Cites* by paper)	DV = log(1 + *Pubs*)		DV = log(1 + *Att_Cites*)		
		NPubs	*Frac_Pubs*	$\alpha(N) = 1$	$\alpha(N) = 1/\sqrt{N}$	$\alpha(N) = 1/N$
	(3-1)	(3-2)	(3-3)	(3-4)	(3-5)	(3-6)
Department-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Career stage FE	Yes	Yes	Yes	Yes	Yes	Yes
Group size	0.0990***	−0.00582	−0.0688***	0.0919***	−0.00303	−0.0834***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Constant	3.127***	0.864***	0.653***	3.405***	3.253***	3.079***
	(0.17)	(0.05)	(0.03)	(0.19)	(0.18)	(0.17)
Observations	5,964	5,964	5,964	5,964	5,964	5,964
R-squared	0.24	0.136	0.21	0.157	0.16	0.183

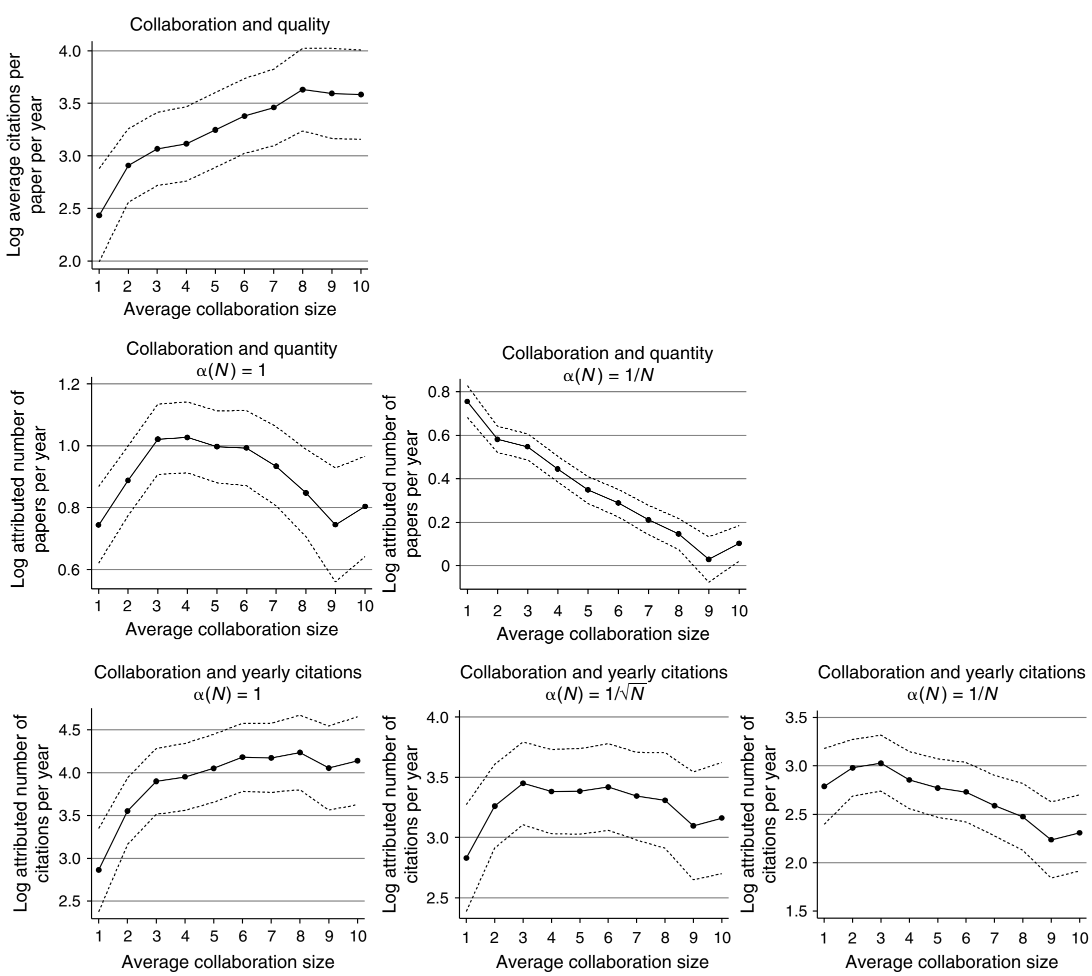
Note. OLS; robust standard errors in parentheses are clustered at the level of the scientist.
***$p < 0.01$.

model (3-3) shows that collaboration is associated on average with lower attributed productivity. In the case of fractional publication counts (3-3), group size is negatively correlated (−0.069).

Finally, models (3-4), (3-5), and (3-6) explore credit attribution from collaboration. Model (3-4) shows that the quality benefit from collaboration is on average superior to its productivity cost where $\alpha(N) = 1$. This result can be interpreted in two ways. First, if one believes that scientists get all the credit for each of their coauthored publication, then scientists might be systematically under-collaborating. A second, more plausible interpretation of the result is that $\alpha(N) < 1$—i.e., that scientists actually do not get full credit for collaborative papers. Models (3-5) and (3-6) propose different credit-sharing functions $\alpha(N)$. $\alpha(N) = 1/\sqrt{N}$ is explored in (3-5) and is consistent with scientists in our data set rationally using collaboration to maximize their yearly attributed impact. Indeed, our model (3-5) shows no statistically significant correlation between collaboration and yearly attributed impact overall. Model (3-6) uses a more strict credit-sharing function in which $\alpha(N) = 1/N$ and shows a statistically significant negative relationship between collaboration and yearly attributed impact. Those results are consistent with our argument that scientists who collaborate cannot claim full credit for the paper they produce. In other words, collaboration entails a cost since credit needs to be split. Perhaps more surprisingly, however, the results also indicate that credit for a given collaborative paper is not shared across coauthors in a way that sums up to 1. In fact, the credit-sharing function in our data seems closer to $\alpha(N) = 1/\sqrt{N}$ all else being equal.

Figure 2 presents the results from the same regressions but with a dichotomized independent variable. Clearly, the hypothesized relationships are nonlinear. The upper left graph shows that the relationship between collaboration and paper quality seems to have decreasing returns and to peak at eight collaborators. The middle row graphs display the relationship between collaboration and productivity for *NPubs* ($\alpha(N) = 1$) and for *Frac_Pubs* ($\alpha(N) = 1/N$). Interestingly, for relatively large collaborations (average coauthoring groups of five or more for the year), the relationship between collaboration and

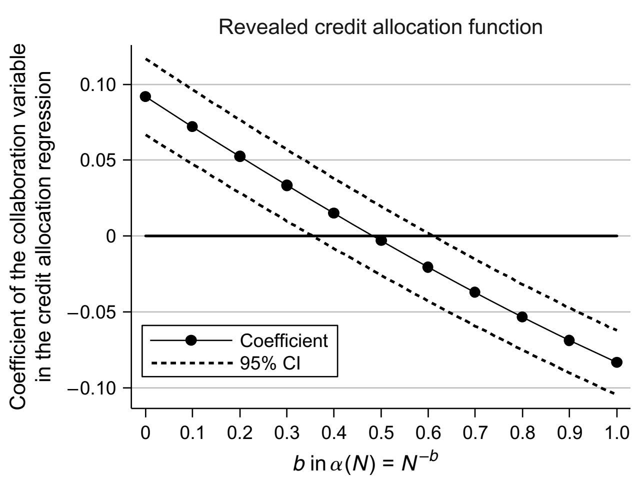
Figure 2 **Relationship Between Collaboration, Quality, Quantity, and Overall Yearly Citations (Estimates)**



productivity is negative for *NPubs* and *Frac_Pubs*. The difference between publication attribution functions comes from relatively small collaboration levels. If coauthors do not "share" credit for the papers they write but instead account for all their papers equally, then collaboration is positively associated with productivity for collaborations of up to three coauthors, on average, per year. However, if papers are split across coauthors, then collaboration is associated with negative (fractional) productivity for every value of N. This result shows that scientists produce fewer papers when they collaborate than when they work alone—but individually, each of them will have more lines on their CV as long as $N < 5$ on average for the year. The bottom graphs also show striking consistencies across $\alpha(N)$ functions. For yearly average collaboration of up to three coauthors, collaboration is associated with more attributed citations. The different results that we observed in models (3-4), (3-5), and (3-6) stem from average yearly group size of four or more. If credit does not get split, then these highly collaborative years are associated with more attributed citations. However, if it does get split, these years are associated with similar levels of ($\alpha(N) = 1/\sqrt{N}$) or fewer ($\alpha(N) = 1/N$) attributed citations.

Figure 3 complements the analysis conducted in models (3-4), (3-5), and (3-6) by examining $\alpha(N) = N^{-b}$ for values of b ranging from $b = 0$ to $b = 1$. First, consider "generous" credit allocation functions such as $\alpha(N) = N^{-0}$ to $\alpha(N) = N^{-0.3}$. Clearly, if these credit allocation functions hold, then scientists under-collaborate, since the coefficient for collaboration in these regressions is positive and statistically significant. As discussed in §3.4, such results would not be completely inconsistent with our theoretical model, but it would indicate that the scientists in our data have considerable difficulty in finding suitable collaborators. Figure 3 that that $\alpha(N) = N^{-0.4}$ and $\alpha(N) = N^{-0.5}$ are consistent with scientists' collaboration choices. In fact, we can estimate that our group size coefficient is closest to 0 for $\alpha(N) = N^{-0.48}$. The 95% confidence interval for b is [0.35; 0.62]. Finally, consider less generous functions $\alpha(N)$ such as $\alpha(N) = N^{-0.7}$ to $\alpha(N) = N^{-1}$. In these cases group size has a negative and statistically significant coefficient, which indicates that scientists might be over-collaborating. As detailed in H3, this result is inconsistent with our framework. We believe that these results provide striking evidence that credit allocation for a given collaborative paper is shared across coauthors and therefore that there is a cost to collaborating. Interestingly, however, this "credit cost" seems relatively small on average, since credit is split in a way that sums to more than 1.

Figure 3 **Imputing $\alpha(N)$ from Scientist' Collaboration Choices**



5.3. Robustness Analysis

Tables A.1 and A.2 in the appendix present additional robustness tests. Our citation-based measure of publication quality could reflect some marketing advantage that larger groups might have. Self-citations in particular are likely to boost the apparent quality of more collaborative papers. Model (A1-1) uses journal impact factor (JIF) as an alternative measure of paper quality and shows that scientists get published in journals of higher impact factor when they collaborate more. Models (A1-2), (A1-3), and (A1-4) examine whether and how authorship position impacts our findings.[11] They assign to a scientist only the publications in which he or she is the last author—and give him or her the entire credit for the publication and resulting citations. Our results are very consistent with those we obtained when using $\alpha(N) = 1/N$. Although fractional measures have been used in bibliometric studies for many years (e.g., Price and Beaver 1996), one could also worry that our results for the case in which $\alpha(N) = 1/N$ might be mechanically driven by the fact that our main independent variable, collaboration, is also in the denominator of our fractional measures of output quantity and overall contribution. This worry, however, is unfounded here because what we are really interested in is precisely whether there are decreasing returns to collaboration. In other words, a negative coefficient in our fractional regressions is evidence of a concave relationship between collaboration and creative output. Models (A2-1) and (A2-2) as well as the left-hand-side graphs presented in Figure 2 (where $\alpha(N) = 1$) further examine this concave relationship. Finally, models (A2-3), (A2-4), and (A2-5) consider only the top 5% of the papers published by department-year and

[11] Note that some of this variance is already accounted for by the fact that we include in all of our models career-stage fixed effects (authorship position is closely related to career-stage).

Table 4 Within MIT Collaboration—Descriptive Statistics

	Publication level ($n = 4,617$ out of 21,054)				Individual-year level ($n = 2,273$ out of 5,964)			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
	Overall group profile							
# PIs	1.26	0.51	1	4	1.27	0.49	1	4
# non-PIs	1.73	1.26	0	10	1.68	1.20	0	10
	Breakdown of collaborating PIs by position of the collaborator							
# junior PIs	0.03	0.19	0	3	0.04	0.20	0	3
# PIs with same position	0.19	0.44	0	3	0.19	0.40	0	3
# senior PIs	0.03	0.20	0	3	0.04	0.20	0	3
	Breakdown of collaborating PIs by department of the collaborator							
# PIs from the same department	0.11	0.33	0	3	0.12	0.33	0	3
# PIs from a different department	0.15	0.40	0	3	0.15	0.37	0	2.5

Table 5 The Effect of PI Collaboration Choices Within MIT

	Quality	Quantity		Credit		
	DV = log(1 + *Cites* by paper)	DV = log(1 + *Pubs*)		DV = log(1 + *Att_Cites*)		
		NPubs	*Frac_Pubs*	$\alpha(N) = 1$	$\alpha(N) = 1/\sqrt{N}$	$\alpha(N) = 1/N$
	(5-1)	(5-2)	(5-3)	(5-4)	(5-5)	(5-6)
Department-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Career stage FE	Yes	Yes	Yes	Yes	Yes	Yes
# PIs	0.196***	−0.0199	−0.297***	0.169**	−0.0945	−0.343***
	(0.07)	(0.02)	(0.02)	(0.08)	(0.08)	(0.07)
# non-PIs	0.119***	0.00134	0.00214	0.121***	0.120***	0.120***
	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)
Constant	1.573***	0.764***	1.042***	1.641***	1.943***	2.232***
	(0.24)	(0.09)	(0.08)	(0.30)	(0.29)	(0.29)
Observations	2,273	2,273	2,273	2,273	2,273	2,273
R-squared	0.245	0.18	0.273	0.221	0.222	0.233

Note. OLS; robust standard errors in parentheses are clustered at the level of the scientist.
$^{**}p < 0.05$; $^{***}p < 0.01$.

show that the general patterns also hold for this subset of publications.

5.4. Different Collaborators

In the subset of 2,273 faculty-years in which MIT PIs publish only with coauthors who were affiliated with MIT, we explore the impact of different types of research collaborators. Table 4 provides the descriptive statistics for this subsample. For these within-MIT years, PIs on average collaborated with 0.3 other MIT PIs and 1.7 non-PIs per year. About half of the inter-PI collaborations (54%) took place between scientists of the same rank, and collaboration took place both within departments and across departments at a similar rate (0.11 and 0.15 collaborating PIs per year, respectively). Table 5 shows that our main results from Table 3 still hold for our subsample of MIT PIs.[12]

Table 6 compares within-department and across-department collaborations. The statistical significance of the differences between the two coefficients is weak,[13] but they are nevertheless suggestive. As compared to within-department collaboration, collaborations spanning departmental boundaries are associated with higher quality output (6-1), lower productivity loss ((6-2) and (6-3)), and overall more credit ((6-4), (6-5), and (6-6)). These results have two possible explanations. On one hand, cross-departmental collaboration might foster the cross-fertilization of ideas while increased specialization limit coordination difficulties. On the other hand, the project selection process might be different for these two types of collaborators. Cross-department collaborators might be more difficult to find. Within-department collaboration might also be partly driven

[12] Note that the coefficients for non-PI in Tables 5, 6, and 7 indicate that the addition of a non-PI coauthor comes at no cost to the PI. This effect is driven by the fact that our fractional measures in these tables do not consider non-PIs (we only divided by the number of PIs).

[13] Wald test of equality between the two coefficients in (6-1): $F(1,548) = 1.85$; p-value of 0.17; in (6-2): $F(1,548) = 1.49$; p-value of 0.22; in (6-3): $F(1,548) = 2.25$; p-value of 0.13; in (6-4): $F(1,548) = 2.48$; p-value of 0.12; in (6-5): $F(1,548) = 2.63$; p-value of 0.11; in (6-6): $F(1,548) = 2.89$; p-value of 0.09.

Table 6 The Effect of PI Collaboration Within and Across Departments

	Quality	Quantity		Credit		
	DV = log(1 + *Cites* by paper)	DV = log(1 + *Pubs*)		DV = log(1 + *Att_Cites*)		
		NPubs	*Frac_Pubs*	$\alpha(N) = 1$	$\alpha(N) = 1/\sqrt{N}$	$\alpha(N) = 1/N$
	(6-1)	(6-2)	(6-3)	(6-4)	(6-5)	(6-6)
Department-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Career stage FE	Yes	Yes	Yes	Yes	Yes	Yes
# PIs from the same department	0.104	−0.0421	−0.323***	0.0488	−0.214**	−0.465***
	(0.10)	(0.03)	(0.03)	(0.11)	(0.10)	(0.10)
# PIs from a different department	0.281***	0.000757	−0.273***	0.282**	0.0175	−0.230**
	(0.10)	(0.03)	(0.02)	(0.11)	(0.11)	(0.10)
# non-PIs	0.116***	0.000517	0.0012	0.116***	0.116***	0.115***
	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)
Constant	1.706***	0.750***	0.749***	1.767***	1.792***	1.819***
	(0.22)	(0.07)	(0.07)	(0.26)	(0.26)	(0.25)
Observations	2,273	2,273	2,273	2,273	2,273	2,273
R-squared	0.246	0.18	0.274	0.222	0.223	0.234

Note. OLS; robust standard errors in parentheses are clustered at the level of the scientist.
$^{**}p < 0.05$; $^{***}p < 0.01$.

by concerns such as friendship or political calculations that do not directly relate to credit maximization. Table 7 distinguishes between junior, senior, and collaborators of the same rank. A prestigious coauthor might increase both the quality and the visibility of the work. On the other hand, senior collaborators might also free ride on the efforts of more junior coauthors. We find evidence consistent with the free-riding mechanism. Collaborating with a more senior colleague does not increase quality (7-1) but does

Table 7 Mechanism—The Effect of PI Collaboration with Different PIs (Within MIT Only)

	Quality	Quantity		Credit		
	DV = log(1 + *Cites* by paper)	DV = log(1 + *Pubs*)		DV = log(1 + *Att_Cites*)		
		NPubs	*Frac_Pubs*	$\alpha(N) = 1$	$\alpha(N) = 1/\sqrt{N}$	$\alpha(N) = 1/N$
	(7-1)	(7-2)	(7-3)	(7-4)	(7-5)	(7-6)
Department-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Career stage FE	Yes	Yes	Yes	Yes	Yes	Yes
		Within department collaboration				
Junior PI	0.18	−0.02	−0.293***	0.14	−0.12	−0.378*
	(0.18)	(0.04)	(0.05)	(0.21)	(0.20)	(0.20)
Same rank PI	0.14	−0.0726*	−0.325***	0.06	−0.18	−0.399***
	(0.13)	(0.04)	(0.04)	(0.14)	(0.13)	(0.13)
Senior PI	−0.19	0	−0.234***	−0.2	−0.411*	−0.612***
	(0.20)	(0.06)	(0.06)	(0.23)	(0.22)	(0.21)
		Across department collaboration				
Junior PI	0.704	0.187	−0.0639	0.996**	0.737	0.502
	(0.47)	(0.12)	(0.12)	(0.50)	(0.48)	(0.45)
Same rank PI	0.671***	0.037	−0.252***	0.733**	0.44	0.162
	(0.26)	(0.07)	(0.06)	(0.30)	(0.29)	(0.29)
Senior PI	−0.0428	−0.00984	−0.232***	−0.0776	−0.341	−0.58
	(0.39)	(0.08)	(0.08)	(0.42)	(0.42)	(0.42)
# non-PIs	0.125***	−0.0000413	−0.00772	0.125***	0.116***	0.108***
	(0.03)	(0.01)	(0.01)	(0.04)	(0.04)	(0.03)
Constant	1.825***	0.739***	0.721***	1.861***	1.881***	1.903***
	(0.22)	(0.09)	(0.08)	(0.29)	(0.28)	(0.27)
Observations	2,273	2,273	2,273	2,273	2,273	2,273
R-squared	0.248	0.182	0.239	0.225	0.227	0.234

Note. OLS; robust standard errors in parentheses are clustered at the level of the scientist.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

impose a cost on productivity (7-3). Scientists appear to perform less well when they collaborate with someone who is senior to them ((7-4), (7-5), and (7-6)). Similarly, collaborations with more junior coauthors do not seem associated with a statistically significant gain in paper quality, but the productivity cost in this case appears considerably lower, leading to relatively more attributed citations.

In sum, the trade-offs associated with collaboration appear to vary with the type of collaborator. Cross-departmental collaborations appear particularly beneficial. The fact that we find evidence of free riding by senior scientists indicates that their junior colleagues might choose to work with them for other reasons than pure credit maximization. Overall, the result that the "credit cost" of collaboration appears to vary across types of collaborations confirms the intuition that $\alpha(N)$ might in reality be complex and vary not only with the size of the research groups but also with their composition.

6. Discussion and Conclusions

Considering collaboration at the level of the individual provides insights into why autonomous creative workers choose to work together or with others having different expertise or different positions in the status hierarchy. As any researcher knows, the decision to collaborate is endogenous, and the focus on creative output (e.g., publications, patents) in prior studies conceals important potential variables that contour collaborative choices. Only through a simultaneous exploration of the benefits and costs of collaboration for individuals can we really seek to understand the phenomenon of collaboration. In this paper, we have taken a step in this direction by developing a theoretical model of collaboration that considers both the potential benefits in terms of productivity and the costs of coordination and credit allocation among individuals. Our empirical focus on individual choices over a period of time enables us to hold "talent" constant, thus overcoming (to some extent), the heterogeneous nature of individual knowledge workers. We thus explore these trade-offs in the organization of scientific work by considering a scientist's decision to allocate her fixed time to more or less collaborative projects.

We find that collaboration is associated with important trade-offs, including higher-quality publications, lower individual productivity and credit shared across collaborators—although in a way that sums up to more than 1. The size of these effects is considerable. A scientist working during a year with one other person on average rather than working alone can hope to receive over 60% more citations per published paper. They will also be able to show more publications on their CVs, despite their fractional productivity having decreased by over 30%, indicating that the two together publish considerably less than they would had they worked separately. Collaboration also means that the scientist will not receive all the credit for what he or she coproduces. In our data, scientists' collaboration behavior is consistent with the scientist receiving "only" around 70%[14] of the credit for the year's output when collaborating with one other person. In addition, the benefits and costs of collaboration vary with the type and number of collaborators. Larger collaborations seem, on average, more costly. In contrast, the benefits of collaborations appear particularly high, and its costs particularly low, when the collaboration brings together individuals having different skills and perspectives—as in the case of cross-departmental collaborations. Interestingly, the drawbacks of collaboration seem especially salient when scientists collaborate with a person who is senior to them.

Collaboration is an increasingly common (and fashionable) organization of work, and a number of studies have highlighted its benefits as a driver of creativity. Its fast spread, however, also brings with it new challenges. For example, coordination difficulties might become more prevalent. The issue of credit allocation in particular has received little attention. For managers and policy makers, collaboration produces a layer of opacity that conceals single contributions and makes rewarding individual performance particularly challenging. As an example, free riding typically is visible to the team members but not to those who evaluate them. This information asymmetry has important implications. It is likely to benefit workers whose reputation is already established while making it more difficult for newcomers to show their value—therefore shaping workers' incentive to take part in collaborative projects. The "net value" of collaboration for credit-seeking workers and for output-focused managers or policy makers might diverge. Our finding that the sum of the shares of credit for a collaborative scientific paper might be greater than one indicates that researchers might get disproportionate credit for collaborative work. As a result, one could imagine that "lone projects" might be neglected. In fact, little is known about credit allocation in collaborative projects, and we hope that our findings will stimulate further research.

This research is not without its limitations. First, the decision to collaborate in smaller or larger groups is a complex one and is likely to involve other considerations than output quality, individual productivity, and credit allocation. For instance, collaboration might be initiated to learn rather than to maximize individual

[14] Percentages were computed using estimates shown in Figure 2. Average credit attribution (yearly citations received) for a collaboration of two when $\alpha(N) = 1$ is 31 citations by 2008. It is 23 citations when $\alpha(N) = 1/\sqrt{N}$.

credit. Second, we are not able to directly measure the scientists' credit allocation function—which is likely to vary substantially across disciplines (Maciejovsky et al. 2009). Instead, we study that function indirectly by first developing a formal model of scientific collaborative choice and then by testing whether its predictions are consistent with the behavior that we observe in our data. Third, absent an experimental design, we cannot be sure that our empirical results are not at least partially driven by task heterogeneity. This endogeneity could be particularly problematic if tasks that can accommodate only large (or small) groups were important in ways that cannot be captured through paper citations or journal impact factor. Nonetheless, our setting offers the advantage of presenting the real choices made by creative workers in a number of scientific disciplines over three decades. Our theoretical model generates predictions that are consistent with scientists' behavior and are robust across a variety of specifications. The fact that our findings are obtained after including individual fixed effects is also important—our approach accounts for the variation in the choices made by the same scientist over the course of their career. Analysis of different types of collaborators further illuminates the various mechanisms underlying the trade-offs that we observe.

Our study is only a first step toward understanding the benefits and drawbacks of collaboration for creative workers. Other correlates are likely to shape a collaboration's net value beyond what we can observe in our data. On the input side, the amount of financial resources and equipment necessary for a given task are likely to vary with group size (Beaver and Rosen 1978). On the output side, collaboration is often described as a particularly enjoyable organization of work and a paramount driver of circulation of ideas, and learning (Katz and Martin 1997). Overall, the relationship between these costs and benefits is likely to depend on the group's intensity, structure, and experience (Porac et al. 2004). These are important nuances that are likely to impact the net value of collaboration and that we have not been able to study here. The importance of continuing research on this topic should not be understated. As the nature of creative work is changing (e.g., von Hippel 2005, Sauermann and Franzoni 2015), more attention might usefully be brought to the fact that in practice, collaboration is an organization of work that brings considerable benefits but that these benefits come at a price.

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Appendix

Table A.1 Robustness Checks (1)

	Journal impact factor	Credit given to last author only[a]		
	Quality	Quality	Quantity	Yearly citations[b]
	OLS; DV = *Average JIF* for the year	OLS; DV = log(1 + *Cites*)	OLS; DV = log(1 + *NPubs*-LastAuthor)	OLS; DV = DV = log(1 + *Att_Cites*-LastAuthor)
	(A1-1)	(A1-2)	(A1-3)	(A1-4)
Department-year FE	Yes	Yes	Yes	Yes
Scientist FE	Yes	Yes	Yes	Yes
Career stage FE	Yes	Yes	Yes	Yes
Group size	0.387***	0.117***	−0.0846***	−0.199***
	(0.06)	(0.02)	(0.01)	(0.02)
Constant	4.456***	2.890***	0.708***	2.832***
	(0.44)	(0.23)	(0.06)	(0.24)
Observations	5,964	2,265	5,964	5,964
R-squared	0.09	0.28	0.16	0.131

Notes. OLS; robust standard errors in parentheses are clustered at the level of the scientist.
[a]Since (total) collaboration is of interest the *Group size* variable was not recalculated to include only last-authored paper.
[b]All cites attributed to last author only.
***$p < 0.01$

Table A.2 Robustness Checks (2)

	Concaveness		Highly cited publications only		
	Quantity	Credit	Credit		
	OLS; DV = $\log(1 + NPubs)$	OLS; DV = $\log(1 + Att\_Cites)$; $\alpha(N) = 1$	OLS; DV = $\log(1 + Att\_Cites)$; $\alpha(N) = 1$	OLS; DV = $\log(1 + Att\_Cites)$; $\alpha(N) = 1/\sqrt{N}$	OLS; DV = $\log(1 + Att\_Cites)$; $\alpha(N) = 1/N$
	(A2-1)	(A2-2)	(A2-3)	(A2-4)	(A2-5)
Department-year FE	Yes	Yes	Yes	Yes	Yes
Scientist FE	Yes	Yes	Yes	Yes	Yes
Career stage FE	Yes	Yes	Yes	Yes	Yes
Group size	0.0492***	0.250***	0.00457**	−0.000532	−0.00247***
	(0.01)	(0.04)	(0.00)	(0.00)	(0.00)
Group size squared	−0.00454***	−0.0130***			
	(0.00)	(0.00)			
Constant	0.782***	3.098***	0.0921***	0.0767***	0.0599***
	(0.05)	(0.21)	(0.03)	(0.02)	(0.01)
Observations	5,964	5,964	5,964	5,964	5,964
R-squared	0.142	0.164	0.041	0.036	0.036

Notes. OLS; robust standard errors in parentheses are clustered at the level of the scientist. The inflection points implied by the coefficients in models (A2-1) and (A2-2) are, respectively, 5.4 and 9.6.
**$p < 0.05$; ***$p < 0.01$.

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