Team Size, Noisy Signals and the Career Prospects of Scientists

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Team production has become increasingly prevalent in organizations. Teams may lead to greater productivity, but they also make it more difficult to distinguish the quality of each contributing team member. We present a formal model and demonstrate that ‘noisier’ signals of quality due to teams have a negative impact. Noisier signals lead to fewer promotions of juniors. High-ability junior workers are more likely to exit the firm, given worse promotion prospects. Noisier signals work in favor of senior incumbents, who are given a wider span of control. Using data from academic science, we show that when the size of scientific teams increased, there is evidence of fewer promotions, more power to senior scientists, and more exit. Thus any productivity gains to the firm from teams must be carefully weighed against their cost in terms of lost information.

Key words: team size, promotions, scientists, careers, economic model

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1. Introduction

One of the most dramatic changes that organizations have experienced over the last thirty years is the rise of teamwork. In the brief period from 1987 to 1999, a survey of Fortune 1000 companies records a jump from 37% to 61% of all firms that now have 20% or more of their employees working in teams (Lawler et al. (2001), and Lawler et al. (1996), compared in Lazear and Shaw (2007)). In the latest nationally representative US survey, in 1994, 52% of all firms now rely on teamwork as a core part of their production (Bandiera et al. (2013)).

The rapid adoption of teams in the last 30 years demonstrates that firms are keenly aware of the benefits of teams. Indeed, managers are aware of both the benefits and costs of teams: increased creativity, combining skills, increased motivation and employee satisfaction, but also the potential for shirking by some team members, and other toxic behavior (Cordery et al. (1991); Hamilton et al. (2012); Jehn and Mannix (2001)). These may be termed “static” benefits and costs: they have an impact on the productivity of the workers today. However, there is a “dynamic” cost of teams
that affects the firm over the long term. This dynamic cost of teams has not been well understood in the academic literature. As a result, it is difficult for managers to make the correct tradeoffs between the benefits of teamwork and its cost, and to correctly assess when and how teams should be implemented.

The dynamic cost of teams is a loss of information. When individuals move to working in teams, their manager is learning less about their abilities, because it is hard to identify individual contributions to the team’s output. As a result, managers find it more difficult to identify the good promotion prospects, particularly among their newer members of staff. Promoting team members will be more risky, because there is a less information available. Currently the academic literature has no predictions for how this will affect the shape of the firm. Firms may respond by promoting fewer people, and maintaining a greater number of reports for each manager; Rajan and Wulf (2006) have evidence that managers now have more direct reports. Firms may instead choose to promote the same number of people as before the advent of teams, and to use re-assignment or separation to deal with those who were incorrectly promoted. The promotion structure in turn will shape the decisions of the individual worker to stay with the firm, or to seek brighter prospects elsewhere. The role of good promotion prospects in keeping bright individuals with the firm is well understood (Deci and Ryan (1985)).

This paper presents the first theory model that predicts how this dynamic cost will shape the firm’s hierarchical structure, its turnover rate, and its overall productivity. We consider a simple model of a firm with a CEO, managers, and each manager’s subordinates. The CEO must make promotion decisions using managers’ assessments of workers’ abilities. Those assessments are imperfect because workers are in teams. Therefore, in each period, as teams’ performance is observed, the CEO is updating her assessment of each worker’s ability. The CEO must also decide how many subordinates to assign to each manager. (We assume that each manager will supervise a number of teams; in this way, the decision on the size of teams is distinct from the decision as to how many subordinates each manager will have.) We posit an exogenous change to the size of teams, possibly because of productivity increases: workers were originally paired in teams of two, and now they are in teams of three. We show that larger teams lead to fewer promotions, because the manager has less information on workers in the team. There are also more erroneous promotions, leading to the promoted worker being demoted or replaced once her/his true quality is better understood. The result is much poorer career prospects, so young workers are more likely to seek work elsewhere, including some with relatively high potential. The firm also responds by assigning many more subordinates to seniors who have been with the firm a long time, and are known to be high quality.
The model highlights that the dynamic cost of teams (in terms of lost information) can have significant impacts on the structure of the firm and on turnover. The information loss will also have significant impacts on firm productivity.

In light of this theory result, is there evidence that the promotion process is seriously affected by relying more on teams? The challenge is to untangle this dynamic effect from the many other forces shaping the modern firm. We argue that academic science provides a uniquely applicable test case for this model. “Bench” science is conducted in laboratories, usually headed up by one scientist, who we will think of as the managerial-level appointment. Academic science has seen a steady increase in teamwork over the decades, so it is an obvious candidate for study. Academic science has two features that render it a very useful test case. First, the increase in scientific teamwork has served to *preserve* productivity over the decades rather than *increase* productivity. Jones (2009) has documented a steady decline in productivity among researchers who work alone, and he shows that researchers who have joined teams have avoided this decline. Thus, aside from the shift to larger teams, the relationship between inputs and outputs in science is relatively steady over time. Thus we can examine this “dynamic cost” in isolation, as it were, and assess its effect on the total output of science. Second, the size of teams is basically independent of the size of laboratories (i.e. the number of direct reports to the “manager”), as it is in the model: many laboratories are large enough to support multiple teams of different sizes, and many teams operate across laboratory boundaries (Adams et al. (2005)). Therefore one can argue that the changes that we see to the size of laboratories in academic science are likely to be a consequence of the dynamic cost that is of interest to us: the effect on promotions of working in larger teams.

The evidence on the evolution of academic science over the last 30 to 40 years appears to support our conclusions. As academic teams have grown, ”star” senior scientists have been attracting a larger and larger share of funding. Fewer young scientists have been awarded enough funding to start their own laboratory. The number of staff per laboratory has grown significantly, as a result. And the promotion prospects of young scientists have grown increasingly dim, with the result that many have exited the world of academic science, and a number have quit science entirely. These trends highlight that the dynamic costs of teams can be considerable, and firms must weigh them carefully against their assessment of the benefits of teams.

The paper proceeds as follows. Section 2 introduces the academic science context and the relevant literature. Section 3 sets up the model, using language specific to science, but the model is applicable to managers and workers more generally. This section includes key theoretical results. Section 4 presents the detailed numerical solution to the model, for two-person teams and three-person teams. Section 4 also identifies the threshold productivity level above which larger teams are still beneficial to the firm. Section 5 presents supporting evidence from available statistical information on turnover, grant allocation and laboratory size in academic science. Section 6 concludes.
2. Background and Literature

2.1. Background and Literature on Academic Science

In academia, laboratory science (or “bench” science) is conducted within relatively hierarchical structures, with similarities to the hierarchy within a firm. A laboratory is headed by one or two senior scientists. The laboratory is staffed with PhD students and post-doctoral students, and in some instances, lab technicians and undergraduates. Many students aspire to head their own laboratory one day; thus academic science is often likened to a tournament, in which many junior staff (the PhD and post-doctoral students) compete, and the prize is a senior position as a laboratory head (Stephan 1996). There is a similar strand of literature on law firms, looking at the competition between law associates to become partners at their firm: see recent work by Ferrall (1996), Galanter and Henderson (2008) and Gershkov et al. (2009).

Funding for the equipment and salaries in the laboratory comes primarily from national funding agencies such as the United States’ National Science Foundation (NSF) and National Institutes of Health (NIH). The Public funding is the largest source of support for science because of the recognized importance of scientific advances for a country’s economic growth (Stephan 2012, chap. 9) and competitive advantage (Gambardella 1992, Cassiman and Veugelers 2006) (Bush 1945)). Competition for grant funding is intense: in 2009, only 22% of applications to NIH were successful (Stephan 2012, Chap. 6). Funding agencies award grants based on both the merit of the proposed research project, and the “track record” (past success in publishing) of the grant applicants. Funding agencies are aware that this gives older researchers a significant advantage, and a number of schemes seek to earmark some funds for younger researchers (Stephan 2012, Chap. 6).

Some national funding agencies restrict applications for large grants to tenure-track and tenured faculty at universities. In other cases, post-docs may apply for large grants (such as the K99-R00 grant from NIH), and winning a such a grant boosts their chances of securing a tenure-track role. Thus the funding decision is implicitly being made by universities and funding agencies together. Universities have gradually found themselves playing the role of an intermediary between the national funding agencies and the laboratory head: the university often provides “seed” money to start a laboratory for a new tenure-track faculty member, but if the faculty member is not successful in attracting subsequent grants, the university will not continue to fund the laboratory (Stephan 2012, Chap. 6). In the extreme, some university positions (even tenured positions) do not include a salary; thus if the scientist is unsuccessful in attracting grant money, s/he is effectively unemployed (Stephan 2012, Chap. 3). Universities have expanded their physical infrastructure and faculty size in periods of greater availability of funding (Stephan 2012, Chap. 5). While the changing roles of universities and funding agencies is an important subject for future work, in our model we will subsume these two roles into one actor, labeled “the funding agency.”
We analyze the trends in science in more detail in Section 5, but we pause here to note one striking trend. Over the last 30 years, scientific laboratories have shifted significantly towards larger and more productive teams (Wuchty et al. 2007) along with greater collaboration across laboratories (Freeman et al. 2014). Greater teamwork leads to a much greater number of names on papers (that is, the credit for scientific work is shared among more scientists). Figure 1, reproduced from Jones (2011), shows the increase in average number of names on papers over time. This trend is visible in all sub-disciplines, including in the theoretical sciences and even in the social sciences. The universality of the trend suggests that the trend is not driven by features of bench science, but that it is a more general phenomenon. The trend is carefully analyzed by Benjamin Jones in his aptly-titled paper “The Burden of Knowledge and the ‘Death of the Renaissance Man’: Is Innovation Getting Harder?” (Jones (2009)). Using a broad range of evidence, Jones demonstrates that this trend is primarily driven by the cumulative nature of knowledge. As more knowledge is accumulated in a field, it takes researchers longer to acquire the knowledge necessary to reach the frontier, and begin to produce knowledge themselves. Researchers respond by specializing in a narrower field of knowledge, and collaborating with other specialized researchers to produce research. Jones shows that researchers who continue to work individually have faced declining productivity, while researchers who collaborate have been able to maintain their productivity.

But this trend towards teams (and larger teams) poses significant challenges for universities and funding agencies as they seek to select promising young researchers. While a high-quality single-authored publication is a relatively clear signal of quality, it is much more difficult to interpret a high-quality publication with ten authors. Certainly there are conventions in the order of authors that provide some information (Stephan 2012, Chap. 4): In the US, in many fields, the convention is that the first author has devoted the greatest number of hours of time to the project, conducting many of the pedestrian tasks necessary to complete a project in bench science. And the final author is generally the head of the laboratory. But these conventions do not provide any clarity as to the source of the interesting insights in the paper. For example, the laboratory head may simply have provided the funding for the project, through funding the salary of the first-author student and any materials or equipment. The ideas may have come from the first-author student, or a collaborating student, or from one of several post-doc students tasked with supervising the student. Conversely, the laboratory head may have played a substantial role in shaping the direction of the project. This information cannot be gleaned from the order of authors on the paper.

2.2. Related Literature on Teams and on Information

The literature on teams is extensive, and it has cataloged a number of important benefits of teams. In terms of benefits, team members striving for a common goal often report a greater sense of
meaningfulness and of participation (Strubler and York (2007)). Combined with the flexibility and social interactions of teams, these attributes can significantly raise employee satisfaction (Cordery et al. (1991)). In addition, there are productivity increases as a result of teamwork (see Sundstrom et al. (2000) for a survey). Teams allow members’ diverse skills to be combined (Hamilton et al. (2012) show that skill diversity increases output). Communication within a team can increase the understanding and acceptance of new ideas (Jehn and Mannix (2001)). The presence of team members can raise the intensity and can create a sense of responsibility, both of which can lead to greater effort (Erez and Somech (1996), Van Dick et al. (2009)).

At the same time the potential costs are significant. In some studies teams have performed worse than individuals: see Gabrenya et al. (1983), Latane et al. (1979); and there are poorly-performing teams even in studies that find productivity increases on average ((Hamilton et al. 2003)). Teams can be “hotbeds of conflict” (Jehn and Mannix (2001)), and relationship conflict damages the performance of the team. Teams can stifle new ideas and lead to “group-think” (Kruglanski and Mackie (1990)). And teams can lead to “social loafing”: employees exert less effort in favor of
socializing or free riding (relying on other team members to exert effort on their behalf) (Liden et al. (2004), Van Dick et al. (2009)).

Interestingly, the benefits and costs identified are all “static” in the sense that they are realized during the life of the team (even if that life is short) in the form of productivity and employee satisfaction. The ever-increasing use of teams in organizations strongly suggests that on balance, firms find that these static benefits of teams outweigh these static costs. For example, one careful study found that output increased by 14% after the adoption of teams (Hamilton et al. (2003)). But the organizational behavior literature has not considered any long-term implications of teams for promotions and career prospects within teams. If the formation of teams hurts the promotion process, this is a “dynamic” cost that the firm may not be taking into account.

There is however a small theoretical literature in economics on how the size of teams affects learning about abilities.\(^1\) Meyer (1994) considers a firm with two young workers and two slightly older workers; each young worker can work with an older worker on a project, or both young workers can work on both seniors’ projects. If observed output is not very “noisy”, we learn more information when young workers don’t form a team. Breton et al. (2003) compare young and old workers working in pairs, and the case of workers working alone; if individual output is noisy, but teams have only team-level noise, then teams can reveal more information in the long run; but this assumption on noise seems counter-intuitive. Ortega (2003) assumes workers work in pairs, and compares effort and learning when one worker takes full responsibility for the project (as a manager) versus shared responsibility in a team; but he only considers learning over one project.

There is also a broader literature on how work design affects how much we learn about workers’ ability (Ortega (2001) and Sliwka (2001)).

Thus far, the economics literature has not drawn out the implications for hiring and retaining talent. (Often these models assume that workers are very short-lived, so they abstract from these considerations.) The effect of different team structures on the promotion prospects of the individual, and her incentives to remain with the firm, have not been considered.

One final strand of literature concerns how market competition affects the firm’s incentives to learn about workers’ ability. The key result is that firms under-invest in learning about ability (see for example Terviö (2009)).\(^2\) We abstract from that consideration here, focusing instead on the

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\(^1\) A separate literature focuses on whether teams form between workers of similar or disparate ability, when learning about abilities is taking place. Anderson and Smith (2010) show that firms will choose to match agents whose ability is better known with workers of less-known ability. We leave this issue for later work, assuming in our model that workers are allocated randomly to teams.

\(^2\) The literature considers how intense competition in the market can reduce the firm’s incentive to invest in learning the worker’s ability (Ghosh and Waldman (2010), Holmström (1999) Macho-Stadler et al. (2014), Terviö (2009), and in a related literature, Taylor (2000)). Harstad (2007) explicitly considers teams in a subsection, but using a structure very similar to Ortega (2003). Workers are in pairs, but if one worker is given responsibility for the project, it is assumed that s/he fully determines its outcome. If competition is not too intense, wages are low and the firm earns profits from high-ability workers; then it pays to identify able workers by giving one worker full responsibility.
impact of team size on learning in the presence of a central funding agency, which plays the role of a social planner. We leave the role of more decentralised players (such as universities) for future work.

3. A Model of Career Progression

3.1. Model Setup

The model lays out a simplified career trajectory in Figure 2. Individuals enter the system by becoming PhD students and then post-doctoral students. One period is the length of time needed to complete a PhD degree or a post-doctoral fellowship, simplified without loss of generality to be identical. After each time period, a postdoc may be promoted to a role as a laboratory head. If she is not promoted, she must decide whether to undertake further study or to exit to an outside option which has a constant wage $\bar{w}$. Thus, the individuals who remain as Ph.D. students or postdocs represent a holding pool, from which each person hopes to be promoted. New students are recruited to replace those who are promoted and those who withdraw from candidature. The decision to become a student is not modeled here, as our focus is on transitions from being a student to being a laboratory head (or exit). Thus we assume that new students can always be recruited to fill available positions.

![Figure 2 The career path](image)

The quality of each individual is assumed to be either 0 or 1. Each student’s quality is not perfectly revealed until she is promoted to be a laboratory head and undertakes her first period
as a lab head. After promotion, once quality is revealed, high-quality lab heads are retained, while low-quality lab heads exit. Incumbent lab heads stay until they retire/die; for simplicity, we assume a constant survival rate across all individuals, of $\delta$ per period.

Individuals do not possess private information about their quality; all information is public. Student $i$ enters with a common prior about her quality, $q_i$, and everyone’s beliefs about her quality are updated as we observe the output of the group she works with. We will describe as the scientist’s ‘type’ as our current beliefs $q_i$ about her quality. We assume that the pool of students is sufficiently large that the distribution of types in the population can be approximated by a continuous distribution, $f(q)$.

The principal in this model is a funding agency. The agency attempts to maximize the output of science, subject to a fixed budget constraint. The funding agency decides which scientists receive enough funding to start their own laboratory, and how big a laboratory. We assume there is just one central funding agency, and that it has the objectives of a social planner, so there are no externalities and incentive concerns. In this section, we also assume that the funding agency is myopic, in the sense that it does not foresee how its allocation of funds today will affect the distribution of available scientists in the next period. To be specific, the funding agency does not consider how its promotion rule affects (1) the decision of students to exit the pool, and (2) the average quality of students in the pool. Thus the funding agency aims merely to maximize the output of science in a given time period. We assume myopia mainly for tractability of the theoretical results. In Section 4 we present simulation results for the case of a fully rational and forward-looking funding agency, and show that it does not change the flavour of the results: As team size increases, the number of promotions decrease, the rate of exit increases, and the lab size of incumbents increases.

The output of a laboratory is shaped strongly by the quality of the laboratory head. If $\theta_h$ is the quality of the lab head, the output of a laboratory in a period is assumed to be

$$\theta_h \sqrt{\sum_{i=1}^{n} \theta_i}$$

which is a concave function of the productivity of teams in her laboratory as measured by the number of people in a team and their quality, $\theta_i$. We choose this functional form for convenience, but any concave function yields similar results. We abstract away from matching in this paper, assuming that students are randomly allocated to laboratories; thus in any period a laboratory has students of the average quality, in expectation. We ignore the role of capital goods, for now, assuming only that there is a constant fixed cost to setting up a laboratory.
In terms of the structure of production, we are comparing two (exogenous) scenarios: one in which the students in a laboratory work in pairs, in which case the production function in (1) becomes

\[ \theta_h \sqrt{\theta_1 + \theta_2} + (\theta_3 + \theta_4) + (\theta_5 + \theta_6) + \ldots \]  

(2)

or the students work in teams of three, in which case the production function in (1) becomes

\[ \theta_h \sqrt{\theta_1 + \theta_2 + \theta_3} + (\theta_4 + \theta_5 + \theta_6) + \ldots \]  

(3)

Notice that the output of the laboratory is identical in these two scenarios, but we will assume that only team output can be observed; so the two production structures have different implications for information. In Section 4 we relax this assumption and allow the three-person teams to have higher output.

3.2. Tradeoffs Faced by the Funding Agency

The funding agency allocates its budget \( M \) across scientists. If \( N \) is the size of the pool of students having \( f(q) \) as their distribution, and \( H \) is the number of (surviving and retained) laboratory heads, the decision in any period is how many of them to promote, and what size of laboratory to give each one. In equilibrium, the funding agency will choose to promote everyone whose probability \( q_i \) of being high-quality is above some threshold \( \bar{q} \). Because survival is a constant probability, the age of the student is not a consideration. Thus the current period maximization problem for the funding agency is simplified to:

\[
\max \quad \delta N_{t-1} \int_{\bar{q}}^{1} q \sqrt{q^n(q)} f(q) dq + H_t \sqrt{q^n(1)} \\
\text{s.t.} \quad \delta N_{t-1} \int_{\bar{q}}^{1} (s + n(q)) f(q) dq + H (s + n(1)) = M
\]

where \( q^e \) is the mean quality of students in the pool, and \( n(q) \) is the number of students assigned to a new lab head of type \( q \). The first term represents the output of science from new laboratories; new laboratory heads are the students \( N_{t-1} \) from last period whose quality was above \( \bar{q} \); they have a distribution of quality from \( \bar{q} \) to 1. The second term represents the incumbent laboratories, who are all of quality 1. The funding agency will allocate different levels of funding to laboratories of different expected quality: an incumbent will receive enough funding to hire \( n(1) \) students (where the "1" indicates the quality of the incumbent) and a new laboratory will receive enough funding to hire \( n(q) \) students. If laboratories are large, in the expected output of the laboratory is approximately a function of the average quality of students, \( q^e \), multiplied by the number of hires.

The budget constraint states that the cost of hiring staff and running laboratories must be equal to the total budget of the funding agency, \( M \), assumed to be constant for simplicity. The fixed cost
of a laboratory is assumed to be a constant value \( s \), and includes the salary of the lab head; the cost of a student’s salary is normalized to 1.

The first-order conditions for this maximization are:

\[
\begin{align*}
0.5 q_e^{-0.5} q n(q)^{-0.5} &= \lambda \\
q_e^{0.5} q n(q)^{0.5} &= \lambda (s + n(q))
\end{align*}
\]

where \( \lambda \) is the Lagrange parameter. These imply:

\[
\frac{q_e^{0.5} n(q)^{0.5}}{s + n(q)} = 0.5 q_e^{0.5} n(q)^{-0.5} \tag{4}
\]

and

\[
qn(q)^{-0.5} = \bar{q} n(\bar{q})^{-0.5} \tag{5}
\]

Equation (4) implies that for the lowest expected-quality laboratory, the marginal productivity is equal to the average productivity. This highlights a key tradeoff faced by the funding agency – it faces an **extensive margin** and an **intensive margin**. Specifically, the agency can lower the quality threshold to fund a larger number of laboratories (of roughly the lowest type) or the agency can increase the number of staff at those laboratories. This tradeoff determines the equilibrium staff levels at the lowest type of laboratory. This decision is independent of the actual value of \( \bar{q} \), the quality threshold above which labs are funded. Solving for \( n(\bar{q}) \) yields a result that does not depend on \( \bar{q} \):

\[
n(\bar{q}) = s \tag{6}
\]

Equation (5) implies that the funding for every other type of laboratory is fixed in proportion to that lowest quality laboratory that is funded. The higher a laboratory’s expected quality, the larger the size of the laboratory:

\[
n(q) = \left( \frac{q}{\bar{q}} \right)^2 s \tag{7}
\]

Equation (7) implies the first proposition:

**Proposition 1:** If a change in the environment causes the funding agency to select a lower value of \( \bar{q} \), incumbent laboratory heads will have larger laboratories than previously.

Based on Equation (7), we can re-write the budget constraint:

\[
\delta N_t \int_q^{q_{t-1}} \left( 1 + \frac{q^2}{\bar{q}^2} \right) f(q) dq + H_t \left( 1 + \frac{1}{\bar{q}^2} \right) = \frac{M_s}{s} \tag{8}
\]
3.3. Dynamic Conditions

We consider the law of motion for students and for lab heads, and we re-write these based on our assumption that the system is in a steady state. First, the total number of students hired must be working in either a “newbie” lab or in an incumbent lab:

\[ N_t = \delta N_{t-1} \int_{q}^{1} n(q)f(q)\,dq + H_t n(1) \]

which gives us the following steady-state relationship:

\[ \frac{H}{N} = \frac{q^2}{s} - \delta \int_{q}^{1} q^2 f(q)\,dq \]  

(9)

Next, the pool of incumbent heads consists of surviving incumbents plus the newly promoted who were retained. The density of new heads of type \( q \) is \( f(q) \), and they are of high quality with probability \( q \), so they are retained with probability \( q \). Thus the law of motion is:

\[ H_t = \delta H_{t-1} + \delta^2 N_{t-2} \int_{q}^{1} q f(q)\,dq \]

which implies that the steady-state relationship is:

\[ \frac{H}{N} = \frac{\delta^2}{1-\delta} \int_{q}^{1} q f(q)\,dq \]  

(10)

3.4. Result: Promoting riskier prospects when there is more uncertainty

Using (9) and (10) to substitute out \( \frac{H}{N} \), we can find an implicit solution for \( \bar{q} \), and from there, \( H \) and \( N \):

\[ \frac{q^2}{s} - \delta \int_{q}^{1} q^2 f(q)\,dq = \frac{\delta^2}{1-\delta} \int_{q}^{1} q f(q)\,dq \]

\[ \Leftrightarrow q^2 = s\delta \int_{q}^{1} \left( \frac{\delta}{1-\delta} q + q^2 \right) f(q)\,dq \]  

(11)

Notice that the left-hand side of equation (11) is monotonically increasing in \( \bar{q} \) and the right-hand side is decreasing in \( \bar{q} \). This implies single-crossing: \( \bar{q} \) exists between 0 and 1 and is unique.3

Equation (11) also indicates how the threshold \( \bar{q} \) will change when there is less information available.

3The particular information structure that we have chosen (to be described below) implies that in each period, a share \( \alpha \) of students will have their quality perfectly revealed to be 1, and only a share \( \alpha^* \) of students will still have an expected quality distributed between 0 and 1. Thus the formula derived in Equation (11) will require a slight amendment for the presence of a positive probability mass at 0 and 1: \( \bar{q}^2 = s\alpha^* \delta \int_{q}^{1} \left( \frac{\delta}{1-\delta} q + q^2 \right) f(q)\,dq + \frac{s\alpha^2}{1-\delta} \). The \( \bar{q} \) still exists and is unique so long as \( \frac{\alpha^2}{1-\delta} \leq 1 \).
Proposition 2: For any change in the environment producing a distribution of expected quality \( f_1(q) \) that is less informative than the original distribution \( f_0(q) \) according to the canonical Blackwell ordering of beliefs (Blackwell 1953), the equilibrium value of \( \bar{q} \) is lower.

Proof: See Appendix 7.1.

Blackwell’s partial ordering states that a distribution of beliefs \( f_0 \) is more informative than a distribution \( f_1 \) if \( f_0 \) is a mean-preserving spread of \( f_1 \). Intuitively, a density \( f_1(q) \) that has more weight near the mean is actually a density with less information: if our belief about student \( i \) is equal to the mean, this means that we have zero information about her particular quality.

In combination with Proposition 1, this now implies a number of results: when there is more uncertainty, there are fewer people about whose quality we are relatively certain. Thus some of the promotions will have to be “riskier”, in the sense that some of those promoted will have very uncertain quality (low expected quality \( q \)). Therefore (from Proposition 1) when there is more uncertainty, the funding agency will also give more funding to the “safe bets”, the incumbent scientists.

3.5. The Updating Process with 2- and 3-person teams

In each period, the output of student teams is observed, and beliefs are updated. We derive the updating process for the case of two-person teams, and compare to the case of three-person teams.

For simplicity we treat each team as occurring within one laboratory, although the model is not affected by having cross-institutional teams. Recall that the output of laboratory \( h \) is a concave function of the productivity of each team, defined as the sum of the qualities in a team:

\[
Y_h = \theta_h \sqrt{\theta_1 + \theta_2} + (\theta_3 + \theta_4) + \ldots
\]

We assume that the productivity of a team is observed, but not the individual qualities within the team. Given that productivity is a 0-1 variable, and we have assumed away uncertainty, the output of a team will be 0, 1, or 2. Thus the individual productivity is perfectly observed if both members are of high quality or both are of low quality. If the total productivity of the team is 1, then one member of the team is of high quality and one member is low quality. Beliefs on quality in those teams are updated according to Bayes’ law: the posterior belief for agent \( a_1 \) is

\[
p_{a_1} = \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)}
\]

We can now think of the updated density of the student population: the cdf of all student teams whose productivity was one is a function \( G \):
\[ G(p) = Pr \left( \frac{q_1(1 - q_2)}{q_1(1 - q_2) + q_2(1 - q_1)} \leq p \right) \]
\[ = Pr \left( q_1 \leq \frac{q_2p}{1 - p - q_2 + 2pq_2} \right) \]
\[ = \frac{1}{2E(q) - 2E(q)^2} \int_0^1 \int_0^{\frac{q_2p}{1 - p - q_2 + 2pq_2}} (q_1 + 2q_1q_2)f(q_1)f(q_2)dq_1dq_2 \] (12)

With this density, we can derive the stable distribution \( f(q) \) of student quality: All students whose current expected quality is above \( \bar{q} \) are promoted, as shown above. And we assume (and prove in subsection 3.6) that all students from \( G(p) \) with quality below a threshold \( q \) exit. Those above the threshold \( \bar{q} \) are promoted. They are replaced with new students. The Appendix details the implicit function defining \( f(q) \) for the case in which the new students are drawn from a uniform \((0,1)\) distribution.

A similar updating process takes place for three-person teams. But now the output of a team can be 0, 1, 2, or 3. Now quality is perfectly revealed if the output is 0 or 3, but not if the output is 1 or 2. Thus there is uncertainty about the quality of many more students in the case of three-person teams. The Appendix provides a definition of \( f(q) \) for three-person teams, again for the case in which new students are drawn from a uniform distribution.

3.6. The Exit Decision of Students

We now turn to consider the exit decision of students. A student compares her continuation value from staying with her continuation value from exiting. We adopt a very simple representation of the outside wage market, and assume that students all expect to find employment in the outside market, and to earn a wage \( \bar{w} \); thus the continuation value of exiting is \( \bar{w} \).

What matters to students is the relative utility from studying, working and being promoted. In order to explore those tradeoffs, we assume for simplicity that a student’s per-period utility from working as a student is 0, and that the per-period utility from working as a laboratory head is 1. And in Section 4, we consider how the results change as we vary the value of \( \bar{w} \). It must be the case that \( 0 < \bar{w} < 1 \), otherwise everyone would exit, or no one.

We consider the decision to stay for those students who are not promoted, i.e. \( q < \bar{q} \). A student with a higher \( q \) has a greater probability that after working in a new team, her updated quality will be above the threshold \( \bar{q} \). Thus the continuation value from staying, \( V(q) \), is higher for a student of higher perceived quality.

We describe the continuation value for the case of two-person teams. In this period, the student of quality \( q_1 \) will be paired with another student, of quality \( q_2 \), drawn from distribution \( f(q) \) described
in the previous subsection. The students earn 0 in this period, so the payoffs below describe payoffs from the following period onward.

- The new team will have output of 2 with probability $q_1 q_2$; then both are known to be high quality. Then the student is promoted and earns $\frac{1}{1-\delta}$.
- The new team will have output of 0 with probability $(1-q_1)(1-q_2)$; then both are known to be low quality. Then the student exits and earns $\frac{w}{1-\delta}$.
- The new team will have output of 1 with probability $(q_1(1-q_2) + q_2(1-q_1))$; then updating takes place as to which has high quality.

- If $q_2 > \frac{q_1(1-q)}{q_1(1-q) + q_2(1-q_1)}$, then the student with quality $q_1$ will not be promoted. Then her continuation payoff is $1 + \delta V \left( \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)} \right)$.
- If $q_2 < \frac{q_1(1-q)}{q_1(1-q) + q_2(1-q_1)}$, then the student with quality $q_1$ will be promoted. But there is still a chance that her true quality will be revealed to be low: so her continuation payoff is $\left[ 1 + \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)} \left( \frac{\delta}{1-\delta} \right) \right] + \frac{q_2(1-q_1)}{q_1(1-q_2) + q_2(1-q_1)} \left( \frac{\delta w}{1-\delta} \right)$.

We are now in a position to calculate the continuation value:

$$V(q_1) = \delta \int_0^1 \left( q_1 q_2 \frac{1}{1-\delta} + (1-q_1)(1-q_2) \frac{\bar{w}}{1-\delta} \right) f(q_2) dq_2$$

$$+ \delta \int_0^{\frac{q_1(1-q)}{q_1(1-q) + q_2(1-q_1)}} \left[ q_1(1-q_2) + q_2(1-q_1) \right] \left[ 1 + \frac{\delta \bar{w}}{1-\delta} + \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)} \left( \frac{1-\bar{w}}{1-\delta} \right) \right] f(q_2) dq_2$$

$$+ \delta \int_{\frac{q_1(1-q)}{q_1(1-q) + q_2(1-q_1)}}^1 \left[ q_1(1-q_2) + q_2(1-q_1) \right] V \left( \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)} \right) f(q_2) dq_2$$

We can now prove that a steady-state equilibrium implies a constant exit threshold:

**Proposition 3:** In any steady-state equilibrium with a constant value of $f(q)$ and a constant promotion threshold $\bar{q}$, the exit decision takes the form of a threshold $\bar{q}$. All students with current perceived quality below $\bar{q}$ exit, and all students with current perceived quality above $\bar{q}$ remain in the pool. This proposition is true for two-person updating and three-person updating.

Proof: See Appendix.

The threshold value $\bar{q}$ will be the value that solves $V(\bar{q}) = \frac{w}{1-\delta}$; in other words, the continuation value is equal to the outside option. We solve for the threshold value of $\bar{q}$ in the numerical simulation.

### 3.7. Results on Cycling

In the model so far, we have assumed that in each new period, a student who was not promoted in the previous period will choose to work with a new team. In other words, a re-shuffling of teams occurs after each period. We now pause to ask whether this is indeed the case, in equilibrium.
Suppose now that at the end of each period, students may choose whether to remain with their current team, or to “cycle” and be assigned to a new team.

**Proposition 4:** Suppose that a team produces an extra output of science $\Delta$ if it has worked together in the previous period. Regardless of how large $\Delta$ is, a student who stays in the pool will choose to “cycle,” that is, to work with a new team this period.

Proof: The output of science does not enter the payoff of the student, only his prospects for promotion. In a stable equilibrium, the cutoff level of perceived quality is constant. Thus, if his perceived quality is below that threshold in this period, the only way to move above that threshold is to update his signal of quality. No additional information can be gleaned with the current team, thus he will move to a new team.

The implication is that cycling takes place, even if it is highly inefficient for the total output of science. A student will need to work with a new team in each period, to have any chance of promotion.

4. **Simulation Results**

This section presents some brief simulation results. In order to avoid discontinuities, new students are assumed to be drawn from a uniform quality distribution: every new student who begins her studies learns the initial belief $q$ about her quality, and the values of $q$ are uniformly distributed between 0 and 1. For example, of the students whose initial value of $q$ is close to 0.3, 30% will prove to be high quality and 70% will prove to be low quality.

Figure 3 plots the cumulative distribution function $F(q)$ of beliefs for the current pool of students, at the end of a period. Notice that for a share of students, the belief on their quality is $q = 0$, because their team has produced zero output. And for another share of students, the belief on their quality is $q = 1$, because their team has produced full output. Notice that there is certainty about the quality of more students in the case of two-person teams, because there is a higher chance that the team is homogeneous. Comparing the two distributions, moving to three-person teams implies that the distribution of student quality becomes less informative. Thus, as described in Proposition 2, we expect the optimal promotion threshold $\bar{q}$ to be lower for three-person teams.

Figure 4 plots the exit threshold $q_e$ and the promotion threshold $\bar{q}$, hold the laboratory fixed costs constant, and varying the value of the outside wage opportunity. The blue line represents the case of two-person teams, and the red line is the case of three-person teams. As predicted, the promotion threshold is lower for three-person teams, suggesting that the funding agency is forced to take risks and promote more uncertain prospects. The funding agency finds itself forced to take these risks because the paucity of highly likely prospects; in point of fact, the agency is promoting
a smaller number of students, but some are higher-risk. As a result, the “safe bets” will be given larger laboratories. Both mechanisms imply that there will be a lower chance of promotion in the case of three-person teams: the promotion threshold is lower, but fewer students will fall above the promotion threshold. Consequently, there is also a higher exit threshold in the three-person case: while a student whose current measured quality is 0.25 would be content to remain in the pool in the two-person case, in case s/he moves up in the quality rankings, in the three-person case, that student would prefer to exit.

A similar pattern is shown in Figure 5 when we graph the promotion and exit threshold for two-person and three-person teams at a fixed wage rate, considering various exit thresholds. Promotion thresholds are higher for two-person teams, and exit thresholds are lower.

The simulation results confirm the predictions of the theoretical model: larger teams imply worse promotion prospects for junior researchers, and higher rates of exit from science.
5. Empirical Evidence from Academic Science

This section reviews the trends in academic science over the last 30-40 years, to see whether they support the explanation outlined in the model.

5.1. Awarding of Grants to Junior and Senior Scientists

Section 2 described a defining trend in academic science over the last thirty years, the increase in teamwork, and the resulting increase in the number of names on papers (Figure 1). The model predicts that funding agencies would respond rationally to the dearth of information about junior researchers by allocating less funding to those junior researchers. Certainly the evidence strongly supports that over time, less funding is going to junior researchers. Figures 6 and 7 show the age distribution of NIH grant recipients in 1980 and again in 2013. While in 1980 the median researcher age was around 38 years of age, the median age increased gradually, to over 15 years older by
This is an enormous change in the allocation of funding. Older applicants are receiving a greater number of grants, and receiving larger grants than young applicants. For example, from 1998-2010, the NIH invested less in R01 (basic) grants and more in large-project grants (Stephan 2012, chap. 6). Overall, more funding dollars are going towards “safe bets” than young unknowns. Paula Stephan, one of the leading experts in the study of science, comments: “The system, at least in the United States, has particularly failed young investigators” (Stephan 2012, p.149).

One striking instance occurred when the NIH budget was doubled, from 1998 to 2002: “The number of first-time investigators grew by less than 10 percent during the doubling” but the number of investigators with more than one R01 grant grew by one-third (Stephan 2012, chap. 6). Our model would predict such an allocation: given that there is an ‘intensive’ as well as ‘extensive’

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Figure 5  Simulated promotion and exit thresholds for two-person (blue) and three-person (red) teams, depending on the value of fixed costs. Wages held constant at $w = 0.739$. 

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Figures 6 and 7 also include the distribution of medical school faculty, many of whom are the principal applicants for these grants. While faculty have also been getting older, the graph suggests that younger faculty are not successful in obtaining grants.
margin, if more funding becomes available, it pays to increase funding to the safe bets, as well as funding some new researchers.

The majority of the funds allocated to a researcher are devoted to staff. The typical lab at a public university, for example, composed of eight researchers— a faculty principal investigator (PI), three postdoctoral fellows (postdocs), and four graduate students, plus an administrator—has annual personnel costs of just over $400,000 and she estimates remaining lab costs to be $200,000 to $250,000 (Stephan 2012, p.112).

According to the National Science Foundation (2014), in 2014 U.S. PhD granting universities spent $45 billion on direct costs, and $29 billion on salaries, wages and fringe benefits. I exclude from direct costs any funding passed on to sub-recipients, as this sum is not divided between salaries and other costs.
MIT Department of Biology from 1966 to 2000. They show that the average laboratory team size grew from 6 to 12 people over that period (not including the lab head), and that the increase was entirely post-doctoral students. The likely explanation is that NIH funding to these laboratories also doubled over this period (as shown by Conti and Liu (2015)).

### 5.2. Cycling and Exit for Junior Scientists

The implication for a junior scientist is that her chances of eventually reaching the top of the pyramid have diminished greatly over these decades. There are fewer laboratories, with a larger number of staff, relative to the pool of funding, than in prior decades. This change did not go unnoticed in the scientific community. A commission of the U.S. National Research Council described a “growing crisis in expectation that grips young life scientists who face difficulty achieving their career objectives” (National Research Council (1998)). Graduates “join an ever-growing pool” of post-doctoral students, and find themselves in a “holding pattern” (National Research Council
The commission found that the pool of post-fellows and non-tenure-track staff at academic institutions grew five-fold from 1973 to 1995 (from 4,000 to over 20,500), while the number of tenured faculty only doubled. The Commission points out that in 1975, 5 years after a PhD, 11% of survey respondents are in a post-doctoral or other non-permanent position, and by 1995, that percentage has expanded to 38% (National Research Council (1998)). NSF conducts a survey of PhD recipients, 5 years after their PhD. The survey shows that in 1973, large numbers of graduates had settled into tenure-track roles after 5 years (55% in biological sciences and 41% in physics). By 2006, less than 15% of biological sciences PhDs had settled into tenure-track roles after 5 years, and less than 25% in physics ((Stephan 2012, Chap. 7)).

The model also predicts that young scientists will ‘cycle’ across positions, that is, move from one laboratory to another during their series of post-docs. The purpose of this cycling (according to the model) is to work with a diversity of teams so as to generate a clearer signal of one’s quality. In practice, there may be additional reasons for cycling; one benefit of moving to a new laboratory is to learn tacit knowledge or skills belonging to that laboratory. Stephan cites instances of cycling for that reason (Stephan 2012, Chap. 4)). However, this benefit must be weighed against the significant costs of cycling. The materials that a young scientist works with are often the property of the laboratory; in the life sciences, these includes cultures and other proprietary materials that may be costly or impossible to reproduce. Thus a postdoc who moves to a new laboratory must often abandon his current line of research and start over. Cycling therefore potentially involves large losses of discovery, which is both a private and a social cost. To this must be added the personal cost of changing cities or countries (as the other labs in one’s field are often elsewhere). A system that encourages cycling can be very costly. Unfortunately, data on cycling is not available, but anecdotal evidence and the large presence in most OECD countries of post-docs trained elsewhere suggests that it is an important effect (Stephan 2012, Chap. 8)).

The expected result is higher rates of exit for young scientists; more PhD and post-doctoral students will decide that their prospects for advancement and job satisfaction are higher outside of science. “The frustration of young scientists caught in the holding pattern is understandable. These people, most of who are 35-40 years old, typically receive low salaries and have little job security or status within the university” (National Research Council 1998, p.3).

With little prospect for

7 In the life sciences, where salaries are relatively high, the 2010 NIH guidelines indicate $38,000 to $48,000 a year for a post-doctoral student; these are very low rates considering their years of training (cited in (Stephan 2012, ft. 38)) They also work long hours; the average post-doc worked 2650 hours per year in 2006, well over 50 hours per week (Stephan 2012, chap. 4).

As an addendum to the modeling, note that Stephan estimates the per-hour costs of a PhD student to be very closely comparable to that of a post-doctoral student, after adjusting for productivity and hours worked and on-costs (Stephan 2012, chap. 4). Thus it is reasonable to treat their wages as comparable in the model.
advancement, remaining in science becomes unattractive. The risk of greater exit from science has been cause for concern in academic and policy circles (Preston 2004).

Available data on exit from academia is limited, because most surveys of PhD recipients suffer from large attrition. However, by comparing Census data from 1980 to 1990, and Census data from 2000 to American Community Survey data from 2010, we are able to estimate exit rates from academia in a companion paper (see de Fontenay and Lim (2016)). By measuring the number of male scientists\(^8\) aged 25-34 years old in academia in 1980, and the number aged 35-44 in 1990, we can determine how many of that cohort exited over that period. The results must be treated with caution, as the raw number of scientists is small.\(^9\) But the results are striking. Exit rates are high in both periods, but our results show that exit rates are much higher in the later period: Of those aged 25-34 in 1980, 42.9\% had exited ten years later; but of those aged 25-34 in 2000, 54.8\% had exited ten years later. Of those aged 35-44 in 1980, 48.7\% had exited ten years later; but of those aged 35-44 in 2000, 55.4\% had exited ten years later (de Fontenay and Lim (2016)).

5.3. Alternative Hypotheses

The observed patterns in science line up well with the predictions of the model. But what alternative explanations exist for these observed trends?

One explanation often proffered is the increased availability of high-quality post-doctoral students from abroad. The opening of China and improvements in training overseas, combined with the pre-eminence of the United States in academic research, has meant that laboratory heads can access many foreign post-docs. There is some evidence that this has depressed salaries for post-docs, particularly in fields where Chinese PhDs are plentiful. And more affordable post-docs might mean that laboratories choose to staff more of them. One author (Borjas (2006)) considering the period 1993-2001 estimated that US post-doc wages were 40\% lower than they would otherwise be, in the absence of the influx of foreign students. However, because of other factors (such as the response in the form of fewer male PhD students from wealthy countries) real wages of post-docs only fell by 3.8\% in that period (Borjas (2006)). Therefore it is unlikely that these wage reductions could fully explain the doubling of laboratory employment observed by Conti and Liu (2015), for example. And this effect does not explain the dramatic fall in success rates for young researchers.

---

\(^8\) We restrict the sample to male scientists, as the number of female scientists in the early period is too small to be accurate. We consider those who emigrated to the US before 1980 for the first sample period, and before 2000 for the second sample period; but the results will miss those who move abroad for jobs in academic science. For comparability, we restrict attention to those with Master’s degrees or above in 1990, 2000 and 2010, and those with 6+ years of education beyond High School in 1980. Respondents indicated that their occupation was in science, and their industry was “Colleges and University” (de Fontenay and Lim (2016)).

\(^9\) The American Community Survey in 2010 is a 1\% sample of the population. The unweighted number of individuals in the smallest category, those aged 35-44 in 2010, is only 72 persons in 2010.
Another explanation may be that equipment has become more expensive (Collins (2015)). If laboratories must purchase more expensive equipment to be successful in research, grant size will increase. And if funding agencies no longer have the option of “trying out” a young researcher with a small grant, young researchers will get fewer grants. However, a counter-argument points out that working with more expensive equipment does not necessarily imply a larger grant. Many laboratories share the use of such large assets at telescopes, synchrotrons, and supercomputers (Stephan 2012, chap. 5). Even medium-size assets such as gene sequencers are often shared. It is possible that there are obstacles to setting up such sharing arrangements for wider ranges of equipment. The other strong counter-argument is that equipment is on average still a minute share of total costs: in 2014 total direct R&D expenditure at doctorate-granting U.S. universities was $45 billion, of which equipment costs were only $1.9 billion.

The final alternative explanation comes from the work of Jones (2009). The cumulative nature of knowledge implies that it takes longer for researchers to acquire enough knowledge to reach the frontier in any field. Jones demonstrates this point convincingly, and shows that there are two responses: (1) scientists train for longer; and (2) scientists specialize in a more narrow field, and then work in teams to bring together specialized skills. The model indeed is built on the latter observation. Could the first observation be driving the results as well? If young scientists are still acquiring skills rather than producing research, this may explain why they are not successful in securing grants or tenure-track roles. However, a closer look at the data seems to suggest that this ‘age’ effect is not large enough (in years) to account for the change. From 1985 to 1999 the increase in median age of NIH grant recipient was about 10 years (Table DDD). But over that time period, the increase in length of PhDs was less than a year on average (Stephan 2012, chap. 5), and the increase in average ‘age of first invention’ of patent holders (Jones (2009)) increased by one year, from 30.5 to 31.5 years of age.

Thus these alternative explanations, while potentially convincing, do not appear to be of sufficient magnitude to explain the striking trends in academic science over the last few decades.

6. Conclusions

In this paper we study a novel cost of teams. Teamwork, while having significant productivity benefits, can have long-term costs to the promotion process in the firm. Collaboration in a team implies that it is more difficult to identify the high-ability workers, reward them and promote them. This information cost is not measured in the short run, so the firm may not remember to take it into account. But this information cost could potentially be large enough to cancel out the benefits of teams.
A natural question for firms to ask is, “How likely is it that these costs are large, given my particular circumstances?” There are two factors that a firm should consider.

The first is whether there are means of assessing individual performance within the team. If the individual’s contribution to the team can be clearly assessed, then the firm is gathering information about ability and motivation, at the same time as it benefits from teams. Studies have also shown that individuals are less likely to engage in social loafing if their individual contribution to the team is observable (Liden et al. (2004)). So there are multiple benefits to identifying individual performance. The challenge arises when measuring and rewarding individual performance causes the individual to be less motivated by team goals and rewards; in that case, team cohesiveness can be threatened (Courtright et al. (2015)).

The second is the competitiveness of the labor market in this firm’s industry. In an industry fraught with poaching, where high-ability individuals are receive many outside offers, there are low returns to identifying and rewarding high-ability individuals. Identifying a high-ability individual means that the firm will have to invest a great deal more in retaining the individual; so on balance the firm is not much better off. Terviö (2009) and others have shown that the firm should spend less on identifying high-quality individuals in a competitive environment. Therefore, if the labor market in one’s industry is highly competitive, this cost of teams may be safely ignored.

One final consideration is that gathering information is especially important for young employees. There is less uncertainty about the ability and motivation of staff with significant tenure at the firm. So the firm should design its teams, and rotation through teams, to maximize its chances of learning about young workers. A number of firms rotate new workers across several departments, to help the worker learn about the firm; but possibly also to help the firm learn about the worker.

7. Appendix

7.1. Proof of Proposition 2

We are comparing two distributions, \( f_0 \) and \( f_1 \), the latter of which has fatter tails. The promotion threshold \( \bar{q} \) falls in the upper range of the distribution, as it must lie above the mean (otherwise the funding agency would choose to promote brand new students rather than existing students); therefore the promotion threshold \( \bar{q} \) lies in the range over which \( f_0(q) > f_1(q) \), because \( f_0 \) has fatter tails.

Let \( \bar{q}_0 \) be the promotion threshold under density \( f_0 \), and \( \bar{q}_1 \) the promotion threshold under density \( f_1 \). Using the definition of the threshold \( \bar{q} \) in equation (11):

\[
\bar{q}_0^2 = s \int_{\bar{q}_0}^{1} \left( \frac{\delta}{1-\delta} q + q^2 \right) f_0(q) dq > s \int_{\bar{q}_1}^{1} \left( \frac{\delta}{1-\delta} q + q^2 \right) f_1(q) dq = \bar{q}_1^2
\]

because \( f_0(q) > f_1(q) \) over this entire range. Therefore \( \bar{q}_0 > \bar{q}_1 \).
7.2. Implicit function defining the distribution of students in two-person teams

As introduced in section 3.5, once we have derived the distribution of posterior beliefs about students’ qualities, we can construct Recall from equation (11) that:

\[
G(p) = \frac{1}{2E(q) - 2E(q)^2} \int_0^1 \int_0^{q_0} \frac{q_p}{(1 - q_2 - q(1 - 2q_2))^3} (q_1 + q_2 + 2q_1q_2)f(q_1)f(q_2) dq_1 dq_2
\]

The density \( g(p) \) is therefore:

\[
g(p) = \frac{dG(p)}{dp} = \frac{1}{2E(q) - 2E(q)^2} \int_0^1 \left( \frac{(q_2 - q^2)^2}{(1 - q_2 - q(1 - 2q_2))^3} \right) f \left( \frac{q_2}{1 - q_2 - q(1 - 2q_2)} \right) f(q_2) dq_2 \times I(q < q < \bar{q})
\]

\[+(1 - \delta(2E(q) - 2E(q)^2)) \int_0^q \int_0^1 \left( \frac{(q_2 - q^2)^2}{(1 - q_2 - q(1 - 2q_2))^3} \right) f \left( \frac{q_2}{1 - q_2 - q(1 - 2q_2)} \right) f(q_2) dq_2 \]

7.3. Implicit function defining the distribution of students in three-person teams

By a similar reasoning, if students work in groups of 3 rather than groups of 2, then the distribution of student qualities \( f(q) \) has the following form (again assuming a uniform distribution of quality for new students):

\[
f(q) = \delta \int_0^1 \int_0^1 \left( \frac{(1 - q_2)^2 q_2^3 (1 - q_3)^2 q_3^3 (1 - 2q_2 - 2q_3 - 2q_2q_3)^2}{(1 - q_2 - q_3 - q(1 - 2q_2 - 2q_3))^3} \right) f \left( \frac{q_2 + q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3)}{1 - q_2 - q_3 + q_2q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3)} \right)
\]

\[\times f(q_1) f(q_2) dq_1 dq_2 dq_3 I(q < q < \bar{q})
\]

\[+ \int_0^q \int_0^1 \int_0^1 \left( \frac{(1 - \delta(3E(q)(1 - E(q))^2)) q_2^3 (1 - q_3)^2 q_3^3 (1 - 2q_2 - 2q_3 - 2q_2q_3)^2}{(1 - q_2 - q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3))^3} \right) f \left( \frac{q_2 + q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3)}{1 - q_2 - q_3 + q_2q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3)} \right)
\]

\[\times f \left( \frac{q_2 + q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3)}{1 - q_2 - q_3 + q_2q_3 - q(1 - 2q_2 - 2q_3 + 3q_2q_3)} \right) f(q_1) f(q_2) dq_1 dq_2 dq_3
\]

If the quality of new students followed a different distribution than the uniform, the function \( f(q) \) would retain a similar form, but the second integral term would be slightly more complicated.
7.4. Proof of Proposition 3

Students will exit when \( V(q_1) \) is less than their outside option, \( \frac{\bar{w}}{1-\delta} \). We will show that \( V(q) \) is weakly increasing in \( q \) over the entire range. It follows that students will use a “threshold” rule and exit if their value of \( q \) is below some threshold \( q_\star \), such that \( V(q) = \frac{\bar{w}}{1-\delta} \), as for all values below \( q_\star \) staying will worth less than \( \frac{\bar{w}}{1-\delta} \), and for all values above \( q_\star \) staying will worth weakly more than \( \frac{\bar{w}}{1-\delta} \).

We prove monotonicity for the case of two-person updating. The proof for three-person updating is available on request.

First note that, for any value of \( q \), it must be that

\[
\frac{\bar{w}}{1-\delta} \leq V(q) < \delta + \frac{\delta^2 q}{1-\delta} + \frac{\delta^2 \bar{w}(1-q)}{1-\delta} \leq \frac{\delta}{1-\delta}
\]  

(13)

That is, the expected utility of staying in the student pool is less than the utility of being promoted to laboratory head after one period (after which the probability of being retained is \( q \)), as the student earns 0 while in the pool. And the expected utility of staying is greater than or equal to the outside option, otherwise the student would exit and then \( V(q) = \frac{\bar{w}}{1-\delta} \).

\[
V(q_1) = \begin{cases} 
\text{Min}(\frac{\bar{w}}{1-\delta}, W(q_1)) & \text{if } q < \bar{q} \\
1 + \frac{\delta q}{1-\delta} + \frac{\delta \bar{w}(1-q)}{1-\delta} & \text{if } q \geq \bar{q}
\end{cases}
\]

\[
W(q_1) = \delta \int_0^1 \left( q_1 q_2 \frac{1}{1-\delta} + (1-q_1)(1-q_2) \bar{w} \right) f(q_2) dq_2
\]

\[
+ \delta \int_0^{\bar{q}} \left( [q_1(1-q_2) + q_2(1-q_1)] \left[ 1 + \frac{\delta \bar{w}}{1-\delta} + \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)} \delta \left( \frac{1-\bar{w}}{1-\delta} \right) \right] f(q_2) dq_2
\]

First note that \( V(q_1) \) must be increasing over some of the range of \( q_1 \): when \( q_1 = 0 \), the value of \( W(q_1) \) is below \( \frac{\bar{w}}{1-\delta} \), and therefore \( V(q_1) = \frac{\bar{w}}{1-\delta} \). And when \( q_1 \geq \bar{q} \), \( V \) is above \( \frac{\bar{w}}{1-\delta} \) and clearly increasing.

Taking the derivative of \( W(q_1) \) with respect to \( q_1 \):

\[
\frac{\partial W(q_1)}{\partial q_1} = \int_0^1 \left( q_2 \frac{1}{1-\delta} - (1-q_2) \frac{\bar{w}}{1-\delta} \right) f(q_2) dq_2
\]

(14)

\[
+ \int_0^{\bar{q}} \left( [q_1(1-q_2) + q_2(1-q_1)] \left[ (1-2q_2) \left( 1 + \frac{\delta \bar{w}}{1-\delta} \right) + (1-q_2) \delta \left( \frac{1-\bar{w}}{1-\delta} \right) \right] f(q_2) dq_2
\]

(15)

\[
+ \int_0^{\bar{q}} \left( [q_1(1-q_2) + q_2(1-q_1)] \left( 1-2q_2 \right) V \left( \frac{q_1(1-q_2)}{q_1(1-q_2) + q_2(1-q_1)} \right) \right) f(q_2) dq_2
\]

(16)
+ \int_{\tilde{q}(1-\bar{q})}^{1} \frac{q_{2}(1-q_{2})}{q_{1}(1-q_{2})+q_{2}(1-q_{1})} V' \left( \frac{q_{1}(1-q_{2})}{q_{1}(1-q_{2})+q_{2}(1-q_{1})} \right) f(q_{2}) dq_{2} \quad (17)

+ \left( \frac{q_{1}(1-q_{1})}{q_{1}(1-\bar{q})+\bar{q}(1-q_{1})} \right) \left[ 1 + \frac{\delta w}{1-\delta} + \bar{q} \delta \left( \frac{1-\bar{q}}{1-\delta} \right) - V(\bar{q}) \right] f \left( \frac{q_{1}(1-\tilde{q})}{q_{1}(1-\tilde{q})+\tilde{q}(1-q_{1})} \right) \quad (18)

Every line except (19) can be shown to be positive. Note first that the bracket in line (20) is positive because of inequality (13). Next we can re-write the first three lines to show that the sum is positive:

\begin{align*}
&= \int_{0}^{\tilde{q}(1-\bar{q})} \left[ (1-2q_{2}) \left( 1 + \frac{\delta w}{1-\delta} \right) + (1-q_{2}) \delta \left( \frac{1-\bar{w}}{1-\delta} \right) + q_{2} \frac{1}{1-\delta} - (1-q_{2}) \frac{\bar{w}}{1-\delta} \right] f(q_{2}) dq_{2} \\
&+ \int_{\tilde{q}(1-\bar{q})}^{1} (1-2q_{2}) V \left( \frac{q_{1}(1-q_{2})}{q_{1}(1-q_{2})+q_{2}(1-q_{1})} \right) + q_{2} \frac{1}{1-\delta} - (1-q_{2}) \frac{\delta w}{1-\delta} \right] f(q_{2}) dq_{2}
\end{align*}

Simple rearrangement of the first integral shows that the integrand is everywhere positive: \((1 - q_{2}) + (1 - \bar{q}) q_{2} \bar{w} + q_{2} \left( \frac{1-\bar{w}}{1-\delta} \right) \). With the second integral, we consider two cases: If \((1 - 2q_{2}) > 0\), then using (13), the integrand is greater than \((1 - 2q_{2}) \frac{\bar{w}}{1-\delta} + q_{2} \frac{1}{1-\delta} - (1-q_{2}) \frac{\bar{w}}{1-\delta} = q_{2} \left( \frac{1-\bar{w}}{1-\delta} \right) > 0\). If \((1 - 2q_{2}) < 0\), then using (13), the integrand is greater than \((1 - 2q_{2}) \frac{1}{1-\delta} + q_{2} \frac{1}{1-\delta} - (1-q_{2}) \frac{\bar{w}}{1-\delta} = (1-q_{2}) \frac{1-\bar{w}}{1-\delta} + q_{2} > 0\).

Leaves only the integral on line (19); we prove by contradiction that this term cannot be negative. Recall that \(V(q_{1})\) cannot be decreasing over the entire range. Suppose that \(V\) were decreasing over the range \([q_{*}, q_{**}]\), and let \(\bar{q}\) be the value of \(q\) for which \(V'\) is at is lowest negative value. Calculate the derivative at \(q_{1} = \tilde{q}\). Line (19) will be smaller in absolute value than \(V'(\tilde{q})\), because the integral sums over a range less than 1, and is multiplied by terms that are less than 1. Given that the other terms are positive, this would imply \(V'(\tilde{q}) < V'(\tilde{q})\), a contradiction.

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