As Science Evolves, How Can Science Policy?*

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Executive Summary

Getting science policy right is a core objective of government that bears on scientific advance, economic growth, health, and longevity. Yet the process of science is changing. As science advances and knowledge accumulates, ensuing generations of innovators spend longer in training and become more narrowly expert, shifting key innovations (i) later in the life cycle and (ii) from solo researchers toward teams. This paper summarizes the evidence that science has evolved - and continues to evolve - on both dimensions. The paper then considers science policy. The ongoing shift away from younger scholars and toward teamwork raises serious policy challenges. Central issues involve (a) maintaining incentives for *entry* into scientific careers as the training phase extends, (b) ensuring effective *evaluation* of ideas (including decisions on patent rights and research grants) as evaluator expertise narrows, and (c) providing appropriate *effort* incentives as scientists increasingly work in teams. Institutions such as government grant agencies, the patent office, the science education system, and the Nobel Prize come under a unified focus in this paper. In all cases, the question is how these institutions can change. As science evolves, science policy may become increasingly misaligned with science itself – unless science policy evolves in tandem.

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I. Introduction

The role of the individual in science is rapidly changing. Recent literature demonstrates (i) ubiquitous shifts towards teamwork in science, and (ii) decreasing innovative output by younger scholars. This paper will review these facts, consider their explanation, and then consider their implications for science policy. At root, this paper asks a simple question: in light of these substantial shifts in the scientific process, how might science policy evolve?

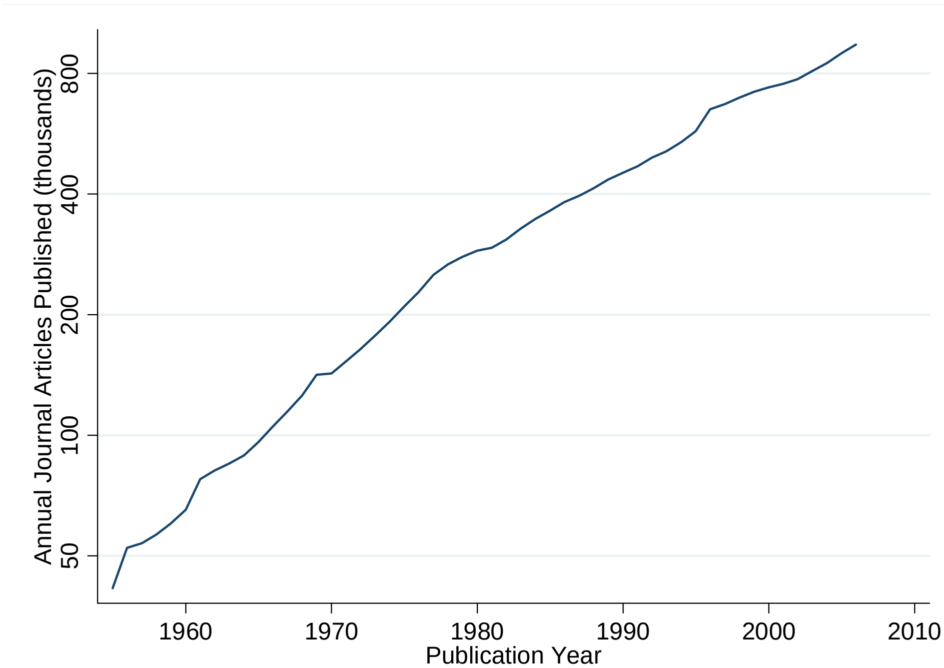
To motivate the basic dynamics in science and frame them in pursuit of rethinking policy, consider the following two observations. First, innovators are not born at the frontier of knowledge; rather, innovators first undertake significant education. Second, if knowledge accumulates and fields deepen over time, then ensuing generations of innovators can face an increasing educational burden. Put another way, if one wants to stand on the shoulders of giants (taking Newton's famous aphorism) then one must first climb up the giants' backs. As knowledge accumulates, the harder this climb can become.

Empirically, one starting point to motivate this 'burden of knowledge' perspective and the associated dynamics in science is to consider knowledge stocks and flows. Figure 1 shows the annual number of journal articles published worldwide.[1] In 2006, there were 941,000 articles published, 90% of which appeared in science and engineering journals. Collectively, these articles cited 4,372,000 unique journal articles published in prior years. It is clear that one individual can know only a fraction of this knowledge. Moreover, assuming that individuals devote a particular amount of time to absorbing knowledge, then it is clear that the fraction of such knowledge known by any one individual will be decreasing with time. As indicated in Figure 1, the growth rate in publications averages 5.5% per year, which doubles collective publication rates every 13 years. If any particular individual meaningfully engages only a fixed

[1] These article counts come from the Institute of Science Information's Web of Science database.

number of such articles, then the fraction of extant knowledge known by an individual would decline at the same rate: -5.5% per year.[2]

Figure 1: Journal Article Publications per Year, Worldwide



Notes: This figure presents the number of publications in each year, worldwide, as recorded by the Institute of Scientific Information's Web of Science database, pooling articles across all fields of science and engineering and social sciences. Growth rates in publications are similar looking only at authors with U.S. addresses. Over 90% of the articles are, consistently, in science and engineering fields. See text for further discussion.

Below we will examine richer and more systematic evidence about the implications of such expansions of knowledge. But it should be clear at this point that innovators face a shifting landscape in which they become educated and produce new ideas. In fact, one may expect two natural responses in innovators' educational decisions as the volume of knowledge expands:

1. First, innovators may spend longer in education;

2. Second, innovators may seek narrower expertise.

[2] That is, let N be the total number of papers (or other codified ideas) in the world and let this number grow at rate g_N. Let Q be the fixed number of papers that an individual has time to learn. Then the share of extant knowledge known by the individual is $s = Q/N$, and the growth rate of s is then $g_s = - g_N$.

The first dimension suggests that innovators would spend a greater portion of their early life-cycle in education – as opposed to actively innovating – so that innovation becomes less likely at young ages. The second dimension, the narrowing of expertise, is essentially a 'death of the Renaissance man' effect. It will tend to reduce the technology-wide capacities of individual innovators, who become less able to draw on knowledge in other fields in their creative process and less capable of implementing ideas by themselves. The narrowing of expertise thus suggests fundamental changes in the organization of innovative activity, with innovators increasingly working in teams. This reasoning suggests potentially powerful shifts in the process of science. In fact, scientists themselves, as will be detailed extensively below, have rapidly and generally evolved in how they produce new ideas, with the probability of signature contributions declining at younger ages and increasing among teams.

Now consider science policy. Science policy bears on scientific progress and the effects of such progress, including advances in economic prosperity, health and longevity. Moreover, as further discussed below, central features of ideas themselves suggest substantial market failures in idea production, so that government policy has explicit roles to play in fostering idea production.

The objective of this paper is to examine how science policy itself might evolve. Given that science is changing, the institutions that are efficient in supporting science at one point in time may be less appropriate at a later point of time. On precise dimensions, a failure to continually re-tune science policy may therefore impede scientific progress.

First, science policy critically influences *entry* into scientific careers. Research agencies like the NIH actively wrestle with why young scientists have become increasingly unlikely to win research grants, which are critical to career progress and success. In fact, former NIH director Elias Zerhouni identified this age trend as the most important challenge for American science and funding agencies (Kaiser 2008). From the burden of knowledge perspective, this age trend follows in part because younger scholars have ever-extending training phases, so that substantial innovative contributions become increasingly unlikely at younger ages. The resulting bias toward older scholars may thus have a strong foundation. On the other hand, lengthening training phases reduce incentives to enter scientific careers. If talented individuals increasingly avoid science in favor of other careers, then scientific progress and economic growth will slow, especially to the extent that other careers do not provide the same positive spillovers for economic prosperity that come via innovation. This selection issue suggests that various kinds of support targeted to the young – though perhaps not major research grants – can provide solutions.

Second, further issues are raised by the increasing narrowness of expertise and the shift toward team production in science. The issues are partly a matter of *evaluating* innovations. The evaluation of ideas is a central role of government that relies on the correct application of expertise within government institutions. Evaluation is necessary ex-post of innovations, particularly in securing intellectual property rights through the United States Patent and Trademark Office (USPTO). Evaluation is also necessary ex-ante of innovations, particularly in allocating limited research grant support through government agencies such as the National Institutes of Health (NIH) and National Science Foundation (NSF). Traditionally, the USPTO has used a single examiner to evaluate and adjust the property rights claims in a patent. The NIH has employed a panel evaluation model within particular study sections, which cover narrowly delimited areas of science. These evaluation models may be increasingly ineffective for assessing broader ideas. While researchers and innovators themselves increasingly use teams (and teams of growing size) that can span broad bodies of knowledge, their research ideas may be constrained by evaluation systems that bring limited breadth of expertise to bear. In fact, the NIH is actively wrestling with a perceived failure to fund "multi-disciplinary" research, and the patent office has experimented with a "Peer-to-Patent" program to better aggregate expertise in evaluating patent applications. These efforts are reacting to consequences of narrowness without necessarily grounding policy initiatives in an underlying framework for how science itself is changing or understanding how general these challenges are. Moreover, as knowledge accumulates, the narrowness of individual expert evaluators will only increase. The basic evaluation challenges, if unmet, suggest increasing difficulties in allocating intellectual property rights and limited public research funds.[3]

[3] Related challenges for journal article evaluation and tenure case evaluation are also relevant but will be left aside here for focus.

Further issues surround the *effort* innovators apply as they respond to the incentives science policy imposes. Evaluation methods that privilege narrow ideas or poorly evaluate broad ideas will constrain ideas with broad impact and direct effort away from work that crosses evaluative boundaries. Grant-giving agencies and tenure systems that privilege narrowness will produce narrowness. Meanwhile, major research prizes, such as the Nobel Prize and the Fields Medal,,remain oriented toward individual accomplishments, which might have been consistent with early 20th Century science but appear increasingly inconsistent with 21st Century science. Individual-oriented rewards encourage individual work and can foment credit conflicts, acting to dissuade teamwork and disrupt team function, even as teamwork has come to dominate science and become the typical locus of high impact ideas.

The rest of this paper is organized as follows. Section II reviews a range of empirical evidence, showing that the role of the individual in science has changed dramatically in line with the 'burden of knowledge' mechanism. Section III considers core roles of science policy, laying the foundation for further analysis. Section IV considers the implications of declining innovative outputs by younger scholars for science policy. Section V considers the implications of the shift to teamwork for science policy. Section VI concludes.

II. The Evolution of Science

This section documents two central dynamics in science. First, innovators have become increasingly unlikely to produce key ideas at younger ages. Second, innovators have become more specialized with time and increasingly work in teams. This section summarizes this evidence and shows that these dynamics follow naturally if knowledge accumulates as science advances.

A. Life-Cycle Productivity in Science

As foundational knowledge expands, innovators may naturally extend their training phases, resulting in a delayed start to the active innovative career. Such a delay may be particularly consequential if raw innovative potential is greatest when young. This section summarizes evidence of this pattern over the 20th century, demonstrating a major dynamic in science: a sharp decline in the innovative output in the early life-cycle.

Table 1: Age Trends

	Trends in Raw Data			Trends with Controls (see notes)		
	Age at Great Achievement		Age at First Patent	Age at Great Achievement		Age at First Patent
	(1)	(2)	(3)	(4)	(5)	(6)
Age Trend (Years per Century)	5.83*** (1.37)	4.86** (2.31)	6.57*** (0.95)	7.79*** (1.54)	8.18** (3.29)	6.71*** (0.99)
Data	Nobel Prize Winners	Great Inventors	U.S. Patent Holders	Nobel Prize Winners	Great Inventors	U.S. Patent Holders
Number of observations	544	286	6,541	544	248	6,541
Time span	1873-1998	1900-1991	1985-1999	1873-1998	1900-1988	1985-1999
Average age	38.6	39.0	31.0	38.6	38.9	31.0
R^2	0.032	0.016	0.007	0.189	0.173	0.020

Notes: All columns present trends in age, measured in years per century. Age at great achievement for Nobelists is the age at which the individual performed their prize-winning work, pooling prize-winners in physics, chemistry, medicine, and economics. For great inventors, age at great achievement is drawn from technological almanacs and covers all major fields of science and engineering. These data are described in detail in Jones (2010). Age at first patent, a different construct, comes from patenting histories for individuals in the United States, observing data since 1975. These data are described in detail in Jones (2009). Columns (1)-(3) present trends in the raw data, i.e. regressing age on time. Columns (4)-(5) present age trends while simultaneously controlling for field fixed effects and country of birth fixed effects. Column (6) presents age trends while controlling for field and patent assignee type fixed effects (e.g. corporation, government lab, et cetera). Robust standard errors for the age trends are given in parentheses. ** Indicates significance at a 95% confidence level. *** Indicates significance at a 99% confidence level.

Table 1 shows basic age trends for three groups. The first group is Nobel Prize winners in physics, chemistry, medicine, and economics. Such individuals have produced their award-winning achievements at increasingly older ages, with the mean age at great achievement increasing by 5.83 years over the 20th century (column 1). The second group is great technological innovators, as listed in technological almanacs documenting major technological breakthroughs through history. The noted breakthroughs have also come at increasingly older ages, with the mean age at great achievement increasing by 4.86 years over the 20th century (column 2). The data and results are described in detail in Jones (2010). The third group consists of more 'ordinary' inventors and considers the age at first patent, using U.S. patent data since 1975 across all technological fields. These individuals show a substantial increase in mean age at first patent, at an equivalent rate of 6.57 years per century (column 3). These data and methods are described in detail in Jones (2009).

The similarity in these age trends, and the fact that they prevail both among great scientists, among great technological inventors, and among more ordinary inventors, point to a general aging phenomenon. As shown in columns 4-6 of Table 1, these raw age trends also persist – and strengthen to 7 or 8 years per century – when controlling for field, country of birth, or the institutional environment of the research. Age trends are also increasing quite generally when examine individual subfields separately,[4] either for great invention or patenting (see Jones 2009 and Jones and Weinberg 2010).

The rise in the mean age of great achievement over the 20th century is dramatic and may represent shifts in research productivity at various phases in the life-cycle. Jones (2010) therefore further analyzes the trends in age at great achievement, locating any shifts in life-cycle research productivity while also accounting for shifts in the underlying population age distribution.[5] As shown in Figure 2A, the analysis shows underlying shifts in life-cycle productivity, beyond any population aging effect. In particular, there is a large decline in the propensity of Nobel Prize winners and great technological inventors to produce great achievements in their 20s and early 30s. Peak productivity has increased by about 8 years, with the effect coming entirely from a collapse in productivity at young ages.

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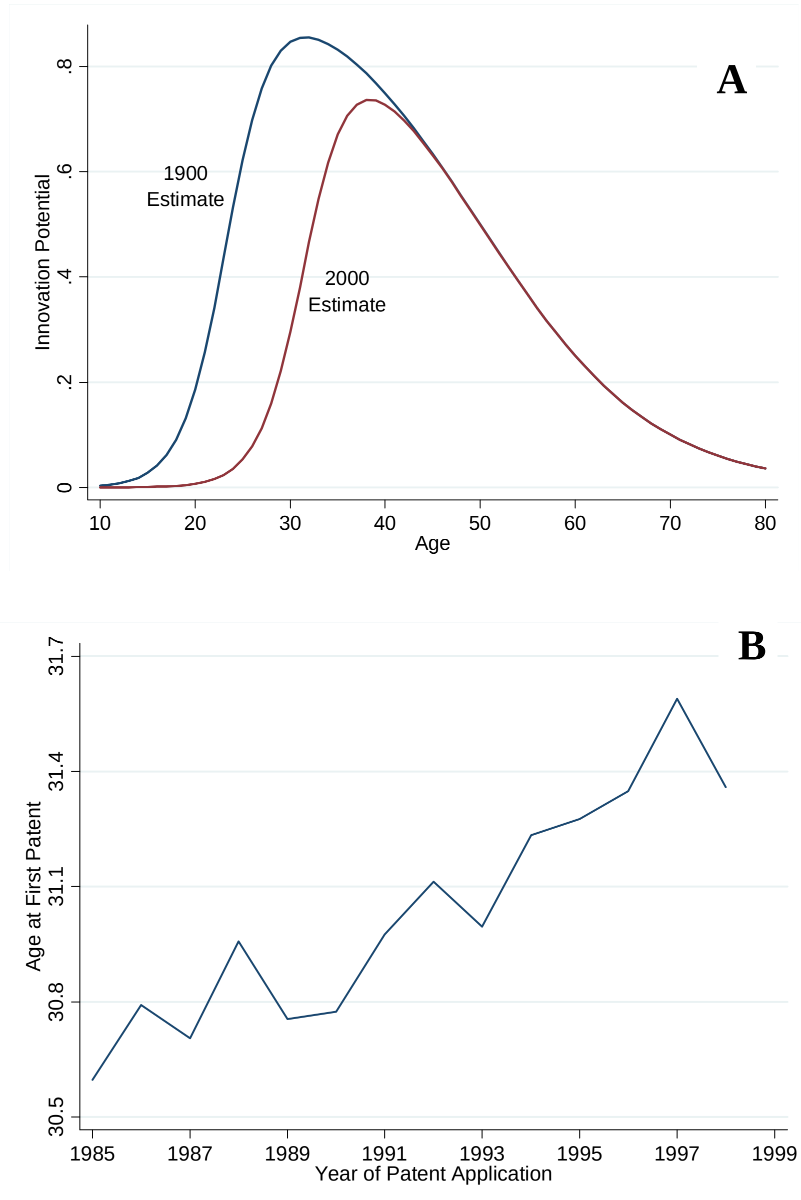
[4] Albeit with some interesting and informative dynamics, as will be discussed below.

[5] The aging trends among Nobel Prize winners and great technological inventors may follow in part from aging of the underlying population distribution. In particular, if there are more scientists alive and active at older ages, then it is increasingly likely that great ideas will come from an older scholar. Jones (2010) shows that about the half of the age trend in Table 1 columns 1 and 2 is driven by the aging population of scholars, while the remaining half is driven by declining research productivity early in the life-cycle. See Jones (2010).

Figure 2: The Decline of Innovation in the Early Life Cycle



Notes: **Fig. 2A** presents an individual's potential to produce great achievements as a function of age, comparing estimates for the year 1900 with the year 2000. The estimates come from analyzing the full set of Nobel Prize winners and great technological inventors over the 20th Century (source: Jones 2010). **Fig. 2B** presents trends in the age at first patent, showing the advance in age at the start of the innovative career, using data on U.S. patent holders (source: Jones 2009). See further discussion in text.

These estimates, showing a substantial, increasing delay in great achievements, closely match the trend in age at first patent among more ordinary inventors. Age at first patent is a more direct measure of early life cycle innovative productivity. The raw trend, analyzed in

Table 1, is further shown in Figure 2B. Coupling Figures 2A and 2B, we see a remarkable consistency across these groups of innovators, suggesting a precise and general phenomenon: a sharp decline in early life-cycle innovative output.

A natural mechanism for declining innovative output in the early life-cycle is a corresponding increase in training duration, which may follow naturally if the foundational knowledge in various fields expands as science advances.[6] This idea can be examined in several ways. First, Table 2 shows that training duration for Nobel Prize winners, measured as mean age at Ph.D., increased by over 4 years over the 20th Century.[7] The role of training duration can be established more causatively by considering exogenous interruptions to young careers. Jones (2010) employs World Wars I and II as such career interruptions and shows that these interruptions must be "made up" after the war, producing both (a) unusual delays in the completion of formal education and (b) unusual delays in the age of great achievement.

Furthermore, Jones and Weinberg (2010) show that the age dynamics in great achievement within Nobel fields closely mirror field-specific dynamics in Ph.D. age. Generally, for Nobel Prize winning work performed prior to 1900, 3 of 4 prize winners had received their Ph.D. by age 25. For Nobel Prize winning work performed since 1980, only 1 of 5 prize winners had a Ph.D. by age 25. Jones and Weinberg (2010) further analyze the effect of an exogenous shock to the foundational knowledge in a field, studying the age and training patterns around the quantum mechanics revolution in physics. The quantum mechanics revolution is typically charted between 1900 and 1927 (e.g. Jammer 1966). Remarkably, we find that (a) age at great achievement and (b) age at Ph.D. actually declined in physics during this period, reaching a minimum just as quantum mechanics becomes a rigorously established theory in the late 1920s and then rising thereafter. Moreover, these patterns are unique to physics; the age of great achievements and Ph.D. age in other fields continued to rise during this period. Viewed as a

[6] By contrast, a Kuhnian revolution in science may be associated with a contraction in the knowledge space, temporarily reducing training requirements. See the discussion of the quantum mechanics revolution below.

[7] Age at Ph.D. is a noisy delimiter of the boundary between a focus on training and a focus on active innovation. That the Ph.D. age trend is somewhat smaller than the trend in age at first patent (an output-oriented delimiter) or age at great achievement suggests that other intermediate institutions, such as the rise of post-doctorates, as well as leaning-by-doing in the innovative process or other features, may involve further delays.

natural experiment, the analysis of the quantum mechanics revolution further substantiates the link between the current depth of knowledge in a field, its training requirements, and the ensuing innovative output of young scholars.

Table 2: Age at Ph.D. Trends

	Dependent Variable: Age at Highest Degree (1)	(2)
Year of Highest Degree (in 100's)	4.11*** (0.61)	4.39*** (0.65)
Data	Nobel Prize Winners	Nobel Prize Winners
Field Fixed Effects	No	Yes
Country of Degree Fixed Effects	No	Yes
Number of observations	505	505
Time span	1858-1990	1858-1990
Average age	26.5	26.5
R^2	0.084	0.283

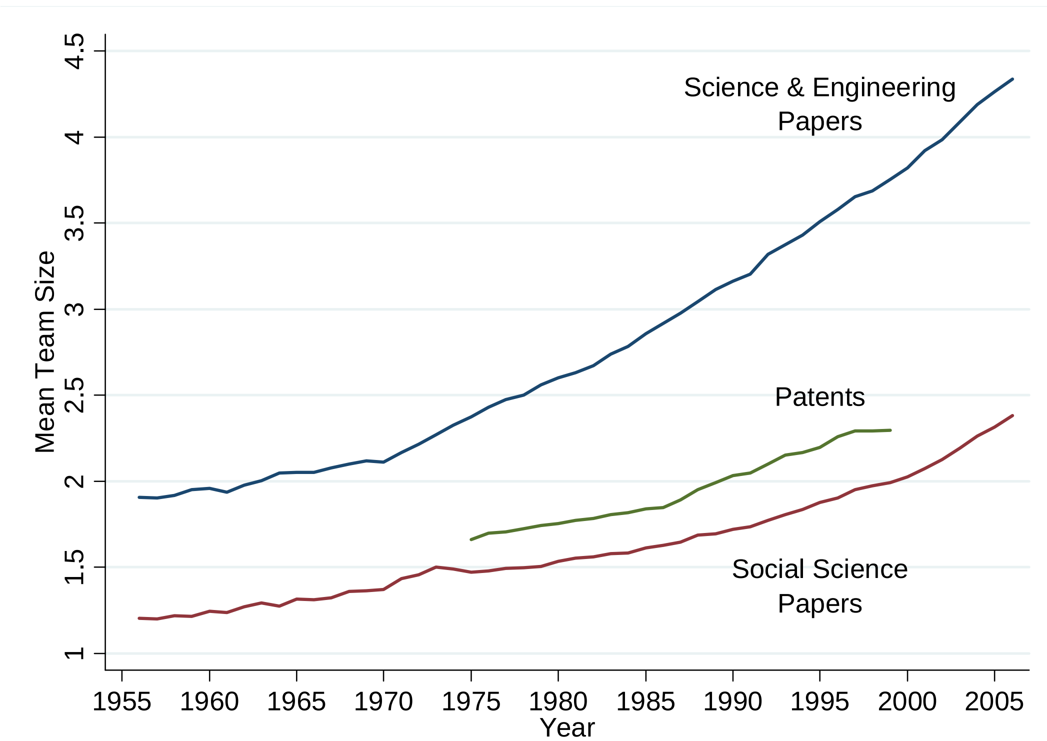
Notes: Both specifications consider trends in the age at highest degree among Nobel Prize winners. The coefficient gives the age trend in years per century. Robust standard errors are given in parentheses. Field fixed effects for Nobel Prizes comprise four categories: Physics, Chemistry, Medicine, and Economics. Source: Jones (2010). *** Indicates significance at a 99% confidence level.

Collectively, we see a tendency toward broad and dramatic declines in early life-cycle productivity among great minds and ordinary inventors, and we see close relationships with increased training duration. Policymakers in some fields – especially in life sciences and at the NIH – have noticed related increases in training duration and a decline in grant awards to younger scholars, and are substantially concerned by these shifts within their field. As has been summarized here, the aging patterns are a much more general phenomenon. Policy implications will be discussed below.

B. Teamwork in Science

Knowledge accumulation further suggests a natural "death of the Renaissance man" effect, where the individual scholar is expert in a narrowing share of scientific and technical ideas as science advances. Narrowing expertise will reduce the capacities of individual innovators to (i) draw on knowledge in other fields in their creative process and (ii) implement broad ideas by themselves. Narrowing expertise thus suggests fundamental changes in the organization of innovative activity, with innovators not only being more specialized but increasingly working in teams. This section documents the second major dynamic in science: a general shift to team production and associated rise of teamwork as the locus of higher impact ideas.

Figure 3: The Ubiquitous Rise in Teamwork



Notes: For papers, the figure plots the mean number of authors per paper across 19 million journal articles indexed by the Institute of Scientific Information's Web of Science database. The Science and Engineering category pools articles from 171 different sub-fields while the Social Sciences category pools articles from 54 sub-fields, as indexed by the Web of Science. For patents, the figure plots the mean number of inventors listed in each patent, using the NBER patent database. For further details see Wuchty, Jones, and Uzzi (2007) and Jones (2009).

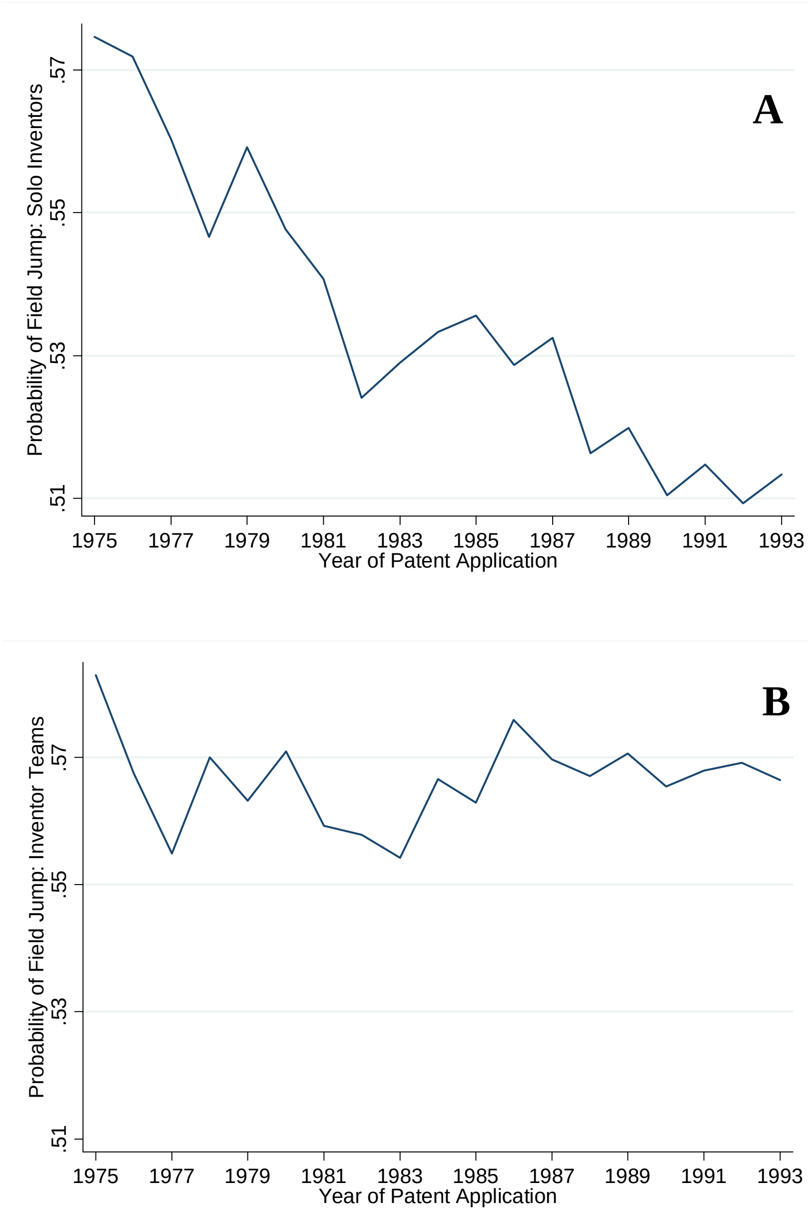
Figure 3 shows the trend toward teamwork in journal articles and patents. The mean number of authors (papers) or inventors (patents) are plotted over time. The journal article data incorporate 20 million publications since 1955 as indexed by the Web of Science. The patent data consider 2.1 million patents issued by the U.S. Patent and Trademark Office from 1975-1999.

We see general increases in teamwork across Science and Engineering journal publications, Social Sciences journal publications, and patenting. Mean team sizes have risen quickly, at rates of 15-20% per decade. The shift toward teamwork also appears in virtually all subfields of research and invention, including 170 of 171 science and engineering subfields, 54 of 54 social science subfields, and 36 of 36 patenting subfields (see Wuchty, Jones, and Uzzi 2007 and Jones 2009). In percentage terms, over 80% of Science and Engineering publications, over 50% of Social Sciences publications and over 60% of patents had multiple authors or inventors by 2005, with the frequency of teamwork rising rapidly in all three areas. As with the life-cycle patterns, we see exceptionally general trends.

Figure 4 presents additional analysis of individual specialization. Figure 4A considers the probability that a solo inventor jumps to a new primary technological field across consecutive patents. A declining tendency to switch fields suggests that individuals are more specialized. Figure 4A shows that solo inventors appear more specialized with time when considering all patenting fields; this tendency also appears in 34 of 36 technology subfields when analyzed separately (see Jones 2009). By contrast, Figure 4B shows that, when operating in teams, inventors move across technological fields with the same frequency over time – so that teamwork appears to overcome the increasing narrowness of individuals.

The relationship between teamwork, specialization, and the depth of knowledge is further supported when comparing fields at a point in time. Comparing across fields, Jones (2009) shows that deeper areas of knowledge are associated with more specialization and more teamwork. Thus, the time trends and the cross-sectional field differences can be interpreted in a consistent and simple manner.

Figure 4: Trends in Specialization: Solo Inventors vs. Team Inventors



Notes: **Fig. 4A** presents the evolution of specialization for solo inventors, plotting the tendency for a solo inventor to switch technological areas across that inventor's consecutive patents. The probability of such field jump declines sharply with time, so that individual inventors appear more specialized, i.e. narrower in their technological span. **Fig. 4B** shows, by contrast, that when individuals work in teams, they jump between fields as regularly as before. Through teamwork, individuals appear to maintain breadth of technological span.

Given that individual scholars and inventors choose whether to work alone or in teams, the increase in teamwork suggests that innovators find teamwork increasingly worthwhile. That teams might have some advantage is further shown in Table 3. First, we see that team-authored papers published between 1995 and 2005 have received more than twice as many citations on average than solo-authored papers. This large citation advantage appears in both Science and Engineering papers and Social Sciences papers. Moreover, when looking at "home run" papers, defined here as those with at least 100 citations, team authored papers are 4.25-4.57 times as likely to produce such "home runs". In patenting, meanwhile, teams are associated with an 18% increase in mean citations received and a 65% increase in the probability of a "home run" patent.

Table 3: Team versus Solo Impact

	Mean Citations Received			Probability > 100 citations		
	Team	Solo	Team/Solo	Team	Solo	Team/Solo
Science and Engineering	11.95	4.55	2.63	1.21%	0.28%	4.25
Social Sciences	8.74	3.31	2.64	0.59%	0.13%	4.57
Patents	6.66	5.64	1.18	0.025%	0.015%	1.65

Notes: This table considers all papers published in the 1995-2005 period (as indexed by the ISI Web of Science and counting citations received through 2007), and all U.S. patents produced in the 1990-1999 period (and counting citations received from other U.S. patents through 2007).

Wuchty, Jones, and Uzzi (2007) further show that the team advantage in citations appears in nearly all sub-fields of Science and Engineering papers, Social Sciences papers, and patents. Moreover, the citation advantage of teams over solo work, and teams' relative probability of home runs, are increasing with time, so that team production appears increasingly privileged in its citation impact. In a number of fields, the team citation advantage reverses what had been a solo-inventor advantage in the 1950s, which emphasizes the changing nature of science and the decline of solo researchers as the locus of the most cited ideas.

In sum, we see general shifts toward teamwork in the production of knowledge, and especially in the production of the most highly cited ideas.

C. Understanding the Evolution of Science

If knowledge accumulation is an intrinsic feature of scientific advance, then the two dynamics in science, documented above, follow naturally. As knowledge accumulates, innovators both extend their training phases and achieve narrower expertise, changing the life-cycle of innovation and the value of teamwork. The empirical value of the knowledge accumulation hypothesis is partly in its generality: it can explain science-wide patterns, ubiquitous across fields and research institutions, both in time series and in cross-section, and aggregate a diverse range of underlying facts under a simple, unifying framework. Knowledge accumulation can thus provide a foundational reason for shifting norms that have been perceived within individual fields, but typically without an appreciation for their generality or an underlying theory of change.[8]

III. Core Roles of Science Policy

Getting science policy right is a key role of government and, arguably, the preeminent role of government in terms of fostering increasing economic prosperity. This claim can be motivated by three mainstream observations in economics. First, a defining feature of the modern age is that certain economies grow and keep growing: the United States has repeatedly doubled its income per person since the Industrial Revolution, leading to unprecedented levels of income and associated increases in health and longevity. Second, this growth comes largely through technological advance – the collective impact of an enormous array of novel ideas. Third, while markets are good at many things, markets face critical failures in the production of new ideas.

The first two observations emphasize the importance of idea creation for economic prosperity. The last observation suggests that government policy can play a critical and even necessary role in encouraging ideas. Indeed, central features of ideas themselves may lead

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[8] Of course, when looking at any particular trend or pattern, other forces may play substantive roles. For focus, this summary leaves aside alternative specific explanations for specific subsets of the facts. Jones (2009), Jones (2010), Jones and Weinberg (2010), Wuchty et al. (2007), and Jones et al. (2008) discuss alternative explanations, and the reader is pointed there for further discussion.

inexorably towards market failures – and particularly to idea *underproduction* in the absence of policy intervention. To frame the analysis of science policy to follow, first consider two core features of ideas, the market failures they cause, and the particular government institutions that exist – and must be well designed - to combat them.

First, ideas are typically harder to create than to copy. More specifically, the production of new ideas involves fixed costs to conceive, develop, demonstrate, and market the idea. If, once this hard work is done, entrants can freely adopt the creation, then the resulting competition will reduce profits from the new idea. This ex-post competition can kill the incentive to produce the idea in the first place, especially to the extent that the innovator cannot recoup the fixed costs of their investment. Intellectual property law, especially patents, serves to limit this ex-post dissipation of profits, thus maintaining incentives for the technological advances that drive economic growth. Patent-granting organizations, such as the USPTO, thus play essential roles in creating well constructed property rights for new ideas.

Second, ideas are often cumulative, building one upon another. To the extent that the creator of the initial idea cannot capture the returns to future creativity that the idea unleashes, the incentive to create an idea may again be insufficiently strong. Patent law also plays a role here: by forcing disclosure of the idea, other innovators are more able to build upon it. But this market failure may be particularly acute for basic research, where new ideas may have little commercial possibility directly but underpin hosts of downstream, commercial innovations. Here, direct government support for basic research (through the university system, government laboratories, and through institutions like the NIH and NSF) may thus also be critical to sustaining idea production and, ultimately, economic growth. In effect, because basic research may provide little direct commercial payoff, the enterprise of basic research – including the researchers themselves - rely importantly on subsidies from public sources.

Given this reasoning, we can consider three key aspects of science policy that the changing nature of science bears especially upon.

1. *Entry*. Scientific and technical progress ultimately relies on the *entry* of talented individuals into scientific careers. To the extent that markets alone do not create

sufficient incentives for entry, science policy is critical to support such career choices. On this dimension, lengthening training phases require special consideration. As research grants and patents come later in the life-cycle, compensation for the delayed start to the career appears needed.

2. *Evaluation*. Effective science policy – both in granting patent rights and granting research support – necessarily relies on the effective *evaluation* of ideas. The increasing challenge for an individual scientist to span broad research areas, as detailed in Section II, suggests the same increasing challenges for government agencies and the individual scientists within them who are tasked with evaluation.

3. *Effort*. Even conditional on choosing a scientific/technical career, the rate and direction of innovator *effort* responds to the incentives science policy imposes. Evaluation methods that privilege narrow ideas, whether in research grants, tenure systems, or elsewhere, will chill efforts to produce ideas with broad impact. Incentive mechanisms that privilege individual researchers, including high-status individual prizes like the Nobel Prize, can undermine teamwork, even as teamwork is increasingly needed for broad impact.

These challenges and possible responses are detailed below.

IV. Rethinking Science Policy: Life-Cycle Issues

The extension of training and decline in early life-cycle innovative output, as detailed in Section II, raise the cost of becoming a scientist. Labor economics provides a useful framework for understanding this cost. In particular, let there be some value V to being a scientist once the necessary training is finished. This value can incorporate the future wage stream, discounted to the moment one starts actively innovating. More generally, the value V could include the expected value of research grants, status, or the simple joy of creativity, all viewed from the moment one begins the active innovative career.

The problem with lengthening training is that it delays receipt of this expected value V. A standard economic model suggests that the cost of one year's delay is about 10% of V. That is, using a discount rate of 10%, it is generally true that a person will value one dollar next year at only 90 cents today. By analogy, a wage stream must rise by 10% to compensate the individual for an extra year of schooling. That this reasoning can apply usefully to labor markets is demonstrated by the fact that average wage returns to an extra year of schooling are about 10%, a relationship that holds in a fairly stable fashion across time and across countries (Mincer 1958, Psacharopoulos 2004).[9,10]

In science, this problem can lead to two straightforward selection effects. First, there is selection across types of scientific careers. While certain areas of science, such as biotechnology, have become increasingly deep, with lengthening Ph.D.'s and the development of post-doctoral phases, other areas of innovation have milder training commitments. Perhaps the most spectacular example in recent years surrounds the "dot.com" boom. In many instances, important innovative ideas, including retail concepts (e.g. book seller + internet), internet search, and HTML software applications required relatively little technical training at first. The relative ease of entry into such innovative careers, other things equal, will tend to draw entrants away from sciences that feature long and extending training phases. Note, however, that this form of selection is not necessarily a concern for scientific and economic progress. Indeed, diverting talent and effort from a harder area of innovation to a less costly but possibly equally fruitful area of innovation may well be efficient.[11]

The second kind of selection effect occurs when talented individuals avoid science entirely. For example, if careers in finance, management, or law require more static levels of training, then scientific careers will be increasingly costly by comparison. The estimated 6-8

[9] The 10% benchmark is true for richer countries. Returns to education tend to be somewhat higher in poorer countries, which is consistent with higher discount rates in poorer countries, as reflected in higher interest rates in poor countries.

[10] The 10% discount rate may not apply perfectly to scientists, who may, for example, particularly enjoy learning or may be especially attracted to non-pecuniary benefits (see, e.g., Stern 2004). Nevertheless, standard discounting likely applies to wage aspects of the scientist's career decision and presumably the individual would, other things equal, rather not delay other benefits as well – whether social status or the joys of creativity and discovery.

[11] Some evidence for this selection effect appears in Table 1. When adding field fixed effects, the age trends rise. This means that the increasing delay is actually higher within individual fields, but that scholars appear to be shifting over time to those fields where great achievements can be had at younger ages.

year delay in becoming an active innovator over the 20th century suggests, at a standard 10% discount rate, a compound 45-55% decline in the value to becoming a scientist. This kind of selection effect may not only slow scientific progress but also slow economic growth, should the positive spillovers that follow from idea creation (see Section III) not feature in other white collar careers. The recent finance boom, drawing talented undergraduates into quickly attained, high wage streams, may make this comparison particularly acute.

A. "Natural" Compensating Mechanisms

Before considering policy mechanisms that can confront this selection issue and encourage entry into science, it is important to evaluate two possible compensating mechanisms that are naturally built into the economy's growth path. The first mechanism is increasing life expectancy. As lifespan increases, the period over which a scientist can enjoy the fruits of their education may extend, raising the value V of being educated. This effect might seem to encourage entry into high-training scientific careers. However, discounting suggests such compensation may be small. In particular, when making career choices in the early life-cycle, an extra year of earnings, prizes, or status 50 years in the future may have little value in comparison to what is immediately foregone. For example, at a discount rate of 10%, an additional year of schooling requires a 10% increase in V to compensate. But an additional year of life 50 years in the future would increase V only incidentally from today's perspective – in fact, by only one half of one percent. Moreover, the increase in life-expectancy is presumably common across types of careers, so this "natural" life-expectancy mechanism has little if any inherent capacity to solve the selection issues above and especially the issue that talented individuals avoid science entirely.

The second compensating mechanism follows naturally as markets expand in size. The value of a patent will tend to increase linearly in the number of people around to use it, and increase similarly as per-capita income rises nationally and globally, raising consumers' willingness to pay. From this perspective, one can assume that, fixing the size of the technological jump embedded in ideas, the market value of a new idea is greater today than in the past. This market size compensation can be substantial and may help explain why we continue to see growing patenting efforts and commercial innovation in equilibrium even as education duration rises and credit is diffused through teamwork.[12]

The "natural" compensation of market size is, however, much less clear for basic research. Unlike patents, the commercial value of a basic research idea (which may typically be zero) does not obviously scale with world GDP, even though the potential value from the idea's downstream spillovers does scale with world GDP. Hence, while the motive to encourage basic research remains extremely strong – and grows -- patent law does not easily transmit this commercial value into basic science. It remains for other institutional forms of support, through agencies like the NIH, NSF, government labs and public universities, to confront the life-cycle challenges and encourage entry into basic science.

B. Policy Mechanisms

To encourage entry into science, one may either (i) increase the value, V, of the scientific career, or (ii) speed up training, to bring V earlier in the life-cycle. This section will consider policy mechanisms that can influence both dimensions.

The value V to being a scientist likely has several important components, including wages, status, and creative freedoms (see, e.g., Stern 2004). To increase V, one could therefore consider several targets. Wages can be increased most obviously through public support of researchers, either in public universities, government labs, or the salary components of research

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[12] In practice, productivity growth, resulting in per-capita income growth, will enhance the market size for ideas but also increase wages in other careers, conveying no innate bias toward innovative careers. However, population growth expands the market size for ideas without affecting wages in other careers directly (according to standard neoclassical growth theory where the aggregate production function is constant returns to scale). So population growth, unlike per-capita income growth, will tend to asymmetrically advantage commercial innovative careers over other careers. We can therefore consider the following back-of-the-envelope calculation. World population growth has averaged approximately 1.5% per year since 1975. Meanwhile, average team size in patenting has risen by 1.1% per year since 1975, suggesting that the individual share of the patents' commercial value falls by about 1.1% per year. The rise in training, at about .08 years annually and with a 10% discount rate, reduces the relative value of an innovative career by 0.8% per year. Thus, assuming that the rate and size of ideas is fixed once the individual is educated, the personal value of the innovative career would be increasing by 1.5% - 1.1% - 0.8% = -0.4% per year. Thus population growth may compensate substantially for the educational challenges in commercially-oriented innovative careers. If we consider a weighted population growth measure, which incorporates rapid increases in relevant technology buyers in China, India, etc, then the compensation will be higher.

grants. To maintain neutrality with other careers, a simple rule of thumb is as follows. If training duration rises by Y years per decade, then with an R% discount rate, V would need to increase RY% per decade relative to the value of alternative careers that do not feature extending training phases. For example, the evidence surveyed in Section II suggests that Y averages about 0.8 years per decade. With a 10% discount rate, V would need to increase by 8% per decade beyond the value increases of other careers. A simple way to achieve this would be to increase salary support by 8% per decade or 0.8% annually above real wage growth in those careers with static training. A closely related alternative would be to increase wage support during the training phase, through graduate student and post-doctoral stipends.[13]

One might also increase V through other dimensions. For example, longer, larger, and/or less restrictive research grants at the height of the scientist's career may be attractive in expectation and help offset the automatic disincentives that emerge as training duration increases. At the same time, forcing grant dollars (not wage support) earlier in the life-cycle looks sub-optimal, in the sense that early-life cycle researchers are less likely to produce important ideas, as shown in Section II.

An additional alternative is to accelerate training. This approach may be especially attractive and of increasing importance if an individual's raw innovation potential is greatest when young. Historically, Figure 2A suggests high innate innovation potential among young scholars (i.e. were training not occupying the individual's time), which is consistent with the broader literature on life-cycle creativity.[14] This finding further amplifies the opportunity costs in the early life-cycle and especially the costs of "busy work" professional apprenticeships, where future innovators are saddled with rote, relatively low skill tasks that have little training value. As one response, science policy might increasingly emphasize a separate track of professionals who focus on rote analytical tasks, requiring less training and without anticipation of being

[13] This discussion emphasizes keeping entry incentives "neutral" with respect to other careers. Of course, one may imagine that research support levels are too low or high in general, and neutrality is meant only as one benchmark.

[14] The capacity for great ideas from young scholars is shown historically in Figure 2A when considering the 1900 estimate. See also Stephan and Levin (1993), Simonton (1998), Weinberg and Galenson (2008), Jones (2010) and Jones and Weinberg (2010) for further discussion.

research leaders. Such training and labor market segmentation could free graduate students and post-doctoral scholars who appear to have strong research potential to migrate more quickly through higher-value training tasks and into active innovation and creative leadership.

More generally, increasing the quality, intensity, and/or focus of training throughout the early life cycle may all bring young scientists more quickly to the knowledge frontier, offsetting the expansion of foundational knowledge and allowing individuals to substitute toward active, high quality innovation at younger ages. The training duration problem thus bears on education policy from childhood and suggests that a central goal of educational policy -- and one of increasing importance -- is to ensure that future innovators are being trained efficiently from very young ages. Achieving such acceleration is a complex matter that requires careful balancing and substantial additional study.[15]

C. The National Institutes of Health Example

An instructive example is the current debates and policy actions at the NIH with regard to early life-cycle research. It has been noticed for years that NIH grants are increasingly given to older researchers as opposed to younger scholars. Between 1970 and 2007, the average age of new investigators (winning R01 equivalent awards) rose from 35 to 42, and the average age among all investigators rose from 41 to 50 (Moore et al., 2008). Elias Zerhouni, the previous NIH director, described this aging trend as the single most important issue for U.S. science; a presumed cause is often claimed to be an increasing bias (for unclear reasons) by older evaluators against younger entrants (Kaiser 2008).[16] The primary response of the NIH has been

[15] The policy issues bear on everything from "free play" formats in early schooling to the "liberal arts" emphasis on knowledge diversity in undergraduate education, both of which may delay the development of expertise. However, because education systems are trying to achieve more than creating narrow expertise, education policy must be careful about what is given up in pursuit of acceleration. For example, students may need time and experience to identify talents and passions, which can make early specialization risky. Educational systems are also trying to instill creativity itself, enhance socialization, build leadership skills, and develop other forms of human capital that may enhance innovative capacity in addition to other life and work skills. At the same time, improving the quality of instruction (including math and science instruction from young ages) creates fewer tradeoffs if such improvements can be had with similar out-of-pocket costs and without taking time from other types of learning.

[16] Whether or not there is a bias of existing scholars against entrants, which is not clear, it is further unclear why such a bias would be increasing with time.

to create quotas, forcing research grants to be given to younger scholars, even when their proposals receive lower evaluation scores.

The smooth trends in NIH grantee age, however, can be understood through increased training duration and demographic shifts. In fact, there is little that is unique about the recent NIH grant age patterns. For example, Nobel Prize winning achievements in physics and chemistry show similarly sized, smooth age dynamics over the late 20th century (Jones and Weinberg 2010). With regard to the biosciences, many observers have noted that doctoral and post-doctoral phases are extending. For example, the duration of the Ph.D. in biosciences rose by 0.9 years per decade between 1970 and 1996.[17] This rate is very similar to the broader delay in innovative careers that was reviewed across many types of research in Section II. Thus part of the decline in early life-cycle innovation can be seen not as an NIH phenomenon or biosciences phenomenon, but as a much more general feature. As shown in Figure 5A, the declining percentage of NIH grants given to scholars age 35 or below follows a broader decline in the share of young medical school faculty members, so that a large part of the trend appears not to be selection within academic scholars but rather the increasing absence of younger academic scholars.[18]

These age shifts are also partly a function of demographics. As Jones (2010) emphasizes, the 20th century aging phenomenon in Table 1 is due partly to a decline in early life-cycle productivity (Figure 2) and partly to the increasing age of the background population.[19] This demographic effect is straightforward: when there are more older scholars around, more ideas will tend to come from older scholars. The baby-boom generation in particular has created a mass of aging scientists in recent decades. In fact, Figure 5B shows that while the percentage of NIH grant recipients age 50 or above has increased dramatically, this trend closely tracks the percentage of medical school faculty age 50 or above, so that we would expect the apparent

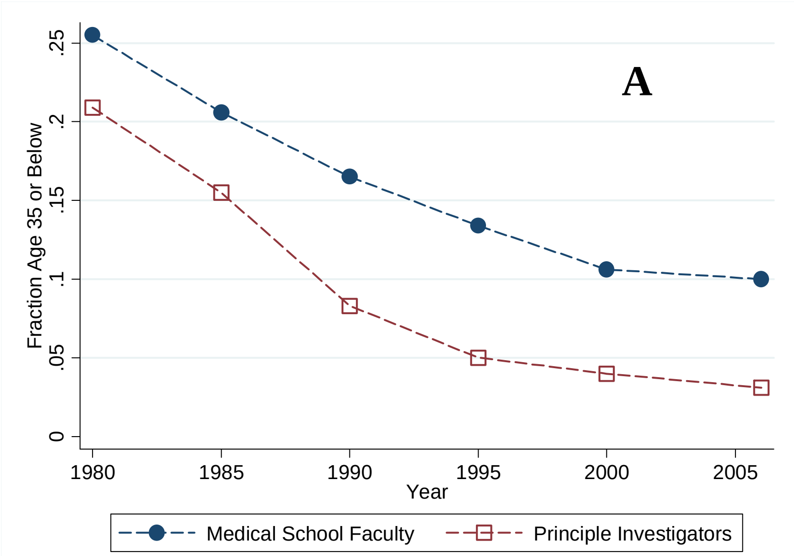
[17] Author's calculations, using data from Tilghman et al. (1998).

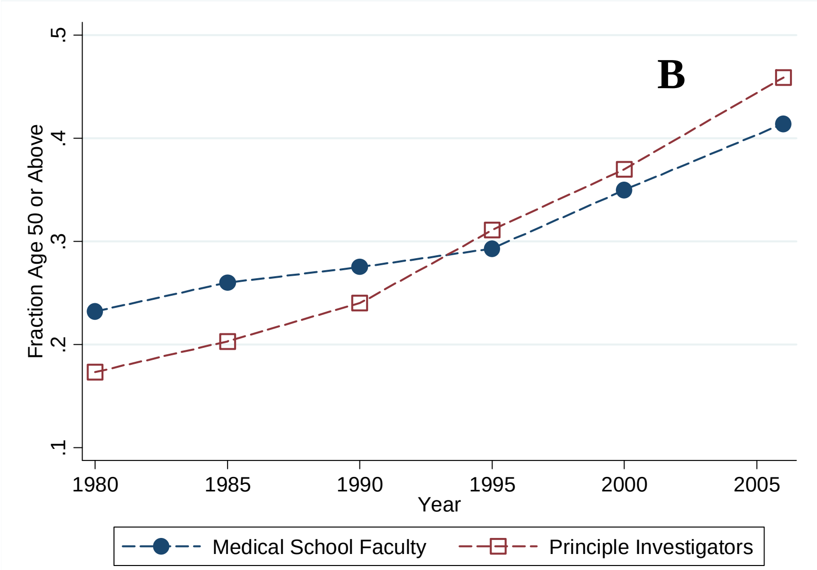
[18] Figure 5 presents the author's calculations using the NIH dataset, "Age Distribution of NIH RPG Principal Investigators Compared to Medical School Faculty, 1980-2006", which is available publicly from http://report.nih.gov/investigators_and_trainees/index.aspx (Access date: 16 March 2010).

[19] See also footnote 5.

"bias" toward scholars over age 50 simply because of demographics. A careful decomposition of these aging patterns requires further detailed analysis, but it should be clear that extending training phases and aging of the innovator population are important contributors, just as they are in understanding broader patterns in invention age over the last century.

Figure 5: Age Shifts for Medical School Faculty and NIH Principle Investigators





Notes: **Fig. 5A** presents the fraction of the indicated group age 35 are younger, tracking these fractions over time. **Fig. 5B** presents the fraction of the indicated group who are at least age 50, tracking these fractions over time.

The NIH policy response to the aging pattern has been quotas for younger grantees. While the motive for this policy - encouraging entry into scientific entry careers - may be well founded, the quota response itself raises serious questions. To the extent that it is increasingly difficult to produce key ideas in the early life-cycle (as suggested by expansions of foundational knowledge, increased training duration, and by observing Nobel Prize winners, great technological inventors, and ordinary patent holders through time), such quotas divert resources to projects with less innovative potential. Increasing wage support for students, post-doctorates, or researchers, or accelerating training, as discussed above, may all act to attract talented individuals to basic research careers without redistributing scarce grant dollars away from top quality proposals.

V. Rethinking Science Policy: Collaboration

Science is shifting universally from an individual to a team production model. This shift, and the associated mechanism by which teamwork can aggregate expertise, raises challenges for how ideas are evaluated by government institutions and, more broadly, how scientists are rewarded for their work.

A. Individual Rewards

There is a storied tradition in science of rewarding particular individuals for remarkable contributions. This tendency is evident in the nomenclature of science, where celebrated achievements historically often carry the scientist's name – Euclidean geometry, Newton's laws of motion, Mendelian inheritance, and the Heisenberg uncertainty principle, to name a few. Furthermore, there are numerous prizes, often with financial and status rewards, that typically if not exclusively tend to emphasize individual contributions, including Nobel Prizes, the Fields Medal, and the A.M. Turing Award, among many others.

To the extent that individual scholars produce great ideas, incentive mechanisms that reward individuals appear to mirror the inventive process. However, as documented in Section II, there has been a ubiquitous shift toward teamwork in science, both as the common format for research and as the organizational locus of the most highly cited work. It does not appear that the reward system of science has caught up with this shift. While individual contributions may still be noteworthy, and individual leadership can be critical to effective team function, rewarding individuals at the expense of teams appears increasingly in tension with the nature of science itself. First, privileging individual rewards creates disincentives to engage in teamwork in the first place, giving individuals reason to horde ideas and avoid partnerships that would enhance the research but dilute credit. Second, in choosing partners, individuals are encouraged to select partners partly based on ex-post credit considerations rather than effectiveness of the research team.[20] Third, researchers end up battling over credit ex-post if the project turns out well, as team members jockey for individual rewards. From this perspective, shifting toward high status and/or financial reward "team prizes" for particular innovations could help undo the incentive challenges that individual rewards impose.

B. Idea Evaluation

The evaluation of ideas matters on two levels. First, given some set of ideas, evaluation matters directly for creating well-defined intellectual property rights and for selecting research lines with high expected payoffs. Second, evaluation expectations affect innovative effort itself. Innovators may choose and/or shape projects that appeal to biases in the evaluative mechanism (affecting the direction of creative activity) and may be dissuaded from innovative effort generally (affecting the rate of creative activity) if the evaluation mechanism is seen as especially noisy.

Because expertise is necessarily limited, evaluation is necessarily challenging. Indeed, how can a single individual evaluate aspects of a patent application or research proposal that sit outside that individual's own expertise? Relying on guesswork will result in error-prone decisions. Relying on a bias against the unknown will privilege narrow ideas. An intuitive response to the increasing teamwork in idea production is to increase teamwork in idea evaluation, engaging multiple individuals that aggregate the necessary expertise. Bringing the relevant evaluative team to bear can increase evaluative accuracy.

[20] This point is an application of the Matthew Effect in science (Merton 1968), which becomes increasingly salient as teamwork becomes increasingly important.

This 'teamwork solution' is not necessarily straightforward, however, and such team-oriented strategies suggest particular features for effective evaluation. First, teams constructed within a narrow field will, by definition, be poorly suited to evaluate ideas that cross the field's boundaries. Thus team evaluation will be most relevant if team structures can be flexibly constituted to evaluate multi-disciplinary ideas. Second, locating appropriate experts is itself challenging, especially when the required expertise is not well understood by the initial evaluator(s). This search problem may create demand for generalists, as opposed to specialists, with broader if shallower expertise and broader social networks.[21] This search problem can also create incentives for 'open science' style evaluation, where the public at large is given incentives to evaluate ideas. However, public evaluation raises a third challenge around disclosure. Especially for early stage evaluation, disclosing a great research idea publicly, thereby allowing others to steal aspects of the idea, may dissuade innovative effort.

C. The United States Patent and Trademark Office

The USPTO has long emphasized a single examiner model. While there are explicit systems of mentoring between senior and junior patent examiners, and some informal teamwork in certain art units (Cockburn et al. 2003), a formal teamwork procedure to aggregate expertise in evaluating and shaping patent claims appears largely absent. Meanwhile, there are ongoing concerns that the patent examiner system misses substantial prior art in its evaluations (see, e.g., Jaffe and Lerner 2004). The recent "Peer-to-Patent" pilot program, which seeks to open prior art searches to the public, is an interesting open-science style approach to tapping aggregate public knowledge. At the same time, it is not clear that the public at large has the incentives (or training) to help much in evaluating patent applications, and those parties who do have strong incentives, such as commercial competitors, may act strategically here. The Peer-to-Patent program also requires earlier public disclosure of the technology, which can run against the patent applicant's private interests and therefore incentives to invent.

[21] The need for generalists, who can span areas of knowledge to improve team member selection and team function (including overcoming communication challenges between team members with distant areas of expertise), is likely growing as specialization narrows. Educational institutions and training systems may need to further adjust to create such generalists. The role of generalists in teams, and its policy implications, awaits further empirical and theoretical study.

An alternative mechanism would continue to rely on internal, professional patent examiners at the USPTO but flexibly form examiner teams for evaluation. In such a model, narrow patent applications might still be assigned to single examiners, while broader patent applications receive scrutiny from examiners in multiple art units. Such a system requires additional coordination, which may be costly. At the same time, by deploying human capital resources so that examiners emphasize only those areas of an application that match their own expertise, this evaluation format may involve less an increase in total examiner time per patent and more a reallocation of time across examiners, leading to potentially mild cost effects but large gains in evaluative accuracy.

D. The National Institutes of Health

The NIH is already team-oriented in evaluations. The standard grant evaluation model employs panels of experts who meet to discuss promising applications collectively. The panel evaluation is traditionally performed within narrowly defined study sections, which aggregate experts within particular knowledge boundaries.[22] This system is presumably effective at evaluating proposals that fall within the panel's expertise. By contrast, it is inherently difficult for any standing panel to effectively evaluate cross-field work, an issue of increasing concern to the NIH. The NIH is now actively working to promote cross-field research, seen as necessary to tackle certain major health challenges and to require a cultural shift within the institute.[23] In addition, the NIH's "Transformative R01 Program" is experimenting in part with a new panel review format that draws on experts in very different fields. Such an evaluative mechanism may be increasingly important as knowledge continues to advance and field expertise narrows. This program is thus consistent with the evolution of science detailed in this paper, which provides a framework for understanding why narrowness has increased, why "multi" or "inter-disciplinary" research may be increasingly important, and how evaluative formats can change in pursuit of funding high impact science.

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[22] Currently, there are 178 distinct, regular standing study sections (see http://www.csr.nih.gov/Roster_proto/sectionI.asp).

[23] See, especially, the "Research Teams of the Future" initiative within the NIH's Roadmap for Medical Research (http://nihroadmap.nih.gov/researchteams/).

VI. Conclusions

This paper shows that the role of the individual in science is rapidly evolving. Teamwork is increasingly dominant in science, while the contributions of young scholars are increasingly rare. These patterns are remarkably general across fields and research institutions, and can be understood as intrinsic to scientific advance, where the accumulation of knowledge naturally results in increasing training duration and narrower expertise.

By perceiving and understanding these patterns, isolated policy reactions to various symptoms can be more carefully founded in the evolution of science itself. This paper has sought to clarify central policy issues, focusing on (a) maintaining incentives for entry into scientific careers as the training phase extends, (b) maintaining effective evaluation of both research proposals and commercial inventions as evaluator expertise narrows, and (c) re-tailoring the reward systems that direct scientific effort as individual accomplishments become rare and team production becomes dominant.

More generally, the analysis suggests an inherent challenge to "status quo" science policy institutions. Because science itself evolves, the appropriate form of science policy at one time will be less appropriate at another. The inertial tendency of institutions makes the implementation of explicitly dynamic science policies challenging, but the stakes are high. This paper has sought to clarify the drag on scientific productivity that static policy institutions may impose and elucidate types of policy adjustments that may accelerate scientific and technological advance.

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