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AGE AND THE TRYING OUT OF NEW IDEAS

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ABSTRACT

Older scientists are often seen as less open to new ideas than younger scientists. We put this assertion to an empirical test. Using a measure of new ideas derived from the text of nearly all biomedical scientific articles published since 1946, we compare the tendency of younger and older researchers to try out new ideas in their work. We find that papers published in biomedicine by younger researchers are more likely to build on new ideas. Collaboration with a more experienced researcher matters as well. Papers with a young first author and a more experienced last author are more likely to try out newer ideas than papers published by other team configurations. Given the crucial role that the trying out of new ideas plays in the advancement of science, our results buttress the importance of funding scientific work by young researchers.

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1. INTRODUCTION

One of the key ways that science advances is by the trying out of new ideas (Kuhn, 1962, 1977; Usher , 1929). While it is widely recognized that normal, non-transformative, science involves the incremental exploration of well-worn ideas, it is also the case that novel ideas – in order to become transformative – require careful and incremental elaboration by scientists. Novel ideas, by their very nature, are poorly understood initially, and thus require much experimentation before the scientific community understands whether and where the new idea is likely to be useful at all. A scientific field is transformed by the trying out of a fruitful, novel idea. Conversely, a new idea in a field that is left alone by that scientific discipline, no matter how brilliant, is almost by definition non-transformative.

Transformative science thus requires considerable tolerance toward the testing of new ideas. This tolerance must extend beyond the scientist who came up with the new idea to other scientists in the field who are willing to lend their time and expertise to trying out the idea. The key is not necessarily how many geniuses there are who come up with new ideas, but rather how many scientists there are who are willing to adopt or try out other people's new ideas. A field advances when there is a critical mass of people who try out a new idea and find it fruitful.

Despite the benefits, there are costs imposed on scientists who try out new ideas. Most novel ideas, no matter how promising at inception, turn out to be less fruitful than hoped. Explaining the potential importance of a new idea is often also difficult, which makes it more difficult to garner grant funding. Indeed, some resistance to new ideas arises because at its infancy a new idea often fits the data more poorly than well-established ideas. Only gradually, if early adopters have found success, do other researchers adopt.

Uncovering the conditions that best encourage the trying out of new ideas is therefore crucial for informed science policy. In this paper, we examine whether scientists who are early in their career are more or less likely to try out new ideas than those who are later in their career. Because teamwork is such an important part of the production of scientific work, as a secondary aim, we examine how the career-stage composition of research teams affects the probability of working on new ideas. We focus our analysis on biomedicine because it is an important area of science and because of the availability of a large database of virtually all journal publications going back to the mid-1940s.

A priori, there are reasons to think that early-stage scientists would be more inclined to try out new ideas (Samuelson, 1946; Holton, 1988). Charles Darwin and Max Planck thought that older scientists in their fields were especially unreceptive to their groundbreaking ideas (Darwin, 1859; Planck, 1936). In an early explanation, it was posited that the minds of older scholars are not as flexible as are the minds of young scholars (Darwin, 1859; Rappa and Debackere, 1993).[1] Scientists closer to graduate school and post-doctoral training are also more likely to be exposed to recent advances, and older scientists may simply have weaker incentives to learn new ideas (Diamond, 1980). Older scientists have also vested interests – intellectual, social, and financial – that may render them less receptive to new ideas (Cohen, 1985). More senior scientists often also have additional demands on their time in the form of committee work, review requests, advising, and other activities, which may limit their willingness to pursue time-intensive work that builds on recent, yet poorly understood, advances. Finally, young scientists may adopt new ideas more often merely because they do not know how unlikely new ideas are to result in success – James Watson went as far as to suggest that knowing too much "kills" you as a scientist (Rappa and Debackere, 1993).

However, *a priori*, there are also reasons why later-career scientists might be more likely to try out new ideas. For instance, if a scientist is tenured, then the career harm from a failed project (which is more likely when trying out a new idea is lower (Edge and Mulkay, 1876). Later-career scientists may also want to avoid a stagnating part of the literature, and may try out new ideas to avoid this problem.

Whether, in fact, early-stage scientists are actually more likely to try out novel ideas is an empirical question on which there is evidence from case studies limited to specific events.[2] By

[1] Some of the more recent work too has proposed that either age itself or the experience that comes with age has direct cognitive impacts on creative capabilities (e.g. Butterfield, 1957; Galenson and Weinberg, 2000; Dietrich and Srinivasan, 2007).

2 The little empirical evidence that exists is mixed. A study on evolution shows a statistically significant negative correlation between age and acceptance of the theory, supporting Darwin's contention that younger scientists were more likely to accept his ideas (Hull et al, 1978). A later re-analysis of the same data finds the link to be small and statistically insignificant (Levin et al., 1995). In three studies on the adoption of new ideas in geology, one study finds support for the idea that older people are slower to adopt a new idea (plate tectonics) in their work (Nitecki et al, 1978), another study on the same idea finds that older scientists were actually quicker in adopting the idea in their work (Messeri, 1988), and a third study finds no link between age and the acceptance of a new idea (continental drift) (Stewart, 1986). A comparison of the age distribution of scientists who adopted a new idea (neural networks) in their work against the age distribution of all scientists finds an overrepresentation of young scientists in the former group (Rappa and Debackere, 1993). An examination of the adoption of a new idea (cliometrics) in

contrast, there is an extensive and systematic empirical literature focused on how age is linked to research productivity as measured by the number of publications, journal rank, citations, grants, or prizes. For instance, a recent review of the literature (Jones et al., 2014) mentions 26 studies on the age–scientific productivity link and just three studies on the age–idea adoption link (one study, Weinberg (2006), belongs to neither group). This disparity is unfortunate because, given the raw nature of initial insights and ideas in science, knowing the conditions under which researchers produce great insights is of little practical relevance unless one also knows the conditions that lead other researchers to further develop the great ideas when the ideas are still in their infancy.

2. METHODS

Our strategy is to analyze all published articles in the biomedical literature. For each publication, we first determine the age of the ideas that the article built upon and the career stage of each author. We then compare the ages of idea inputs across publications to measure how the career stage of the author(s) influences the tendency to build on new ideas. Our primary data source is the MEDLINE database, an indexed database on over 20 million journal articles that covers nearly every biomedical article published since 1946.

We determine the ideas upon which a publication is built from the available text of the publication (title and abstract). By design, this text reveals the ideas that are central to the publication. While some of these ideas are brand new, most are ideas that the research that led to the publication built upon and recombined in a new way. To extract the idea inputs and their vintage, for each publication we construct a list of all words and 2- and 3-word sequences (for example, *cimetidine* and *nitric oxide synthase*) that appear in the text. We also index the year that each idea first appears in the MEDLINE database, in order to calculate the ages of the idea inputs in each paper. [3,4]

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economic history finds that the link between age and adoption of the new idea to be negative but very weak (Diamond, 1980). Finally, an analysis of 28 high-profile scientific controversies from 1500s to 1900s finds a negative link between scientist age and the acceptance of new theories (Sulloway, 2014).

[3] Just because a new idea is found first in a paper in our database does not necessarily mean that the idea originated with the author(s) of the paper. It is possible that the idea originated outside biomedicine, for instance, and is not indexed in the MEDLINE data. At best we can infer that the authors are trying out that idea, which of course is the

Our list of the popular idea inputs – identified by this approach – is dominated by ideas that are easily recognized as having been important building blocks for biomedical research in recent decades (*Web Appendix*, Table S1). The list includes new methodologies (e.g. *polymerase chain reaction*), new pathologies (e.g. *HIV*), new molecules (e.g. *caspase-3*), new interpretations about causes for pathology (e.g. *h. pylori*), new biological pathways (e.g. *small interfering RNAs*), and advances in physical chemistry applied to biology (e.g. *b3lyp*), among many other categories of new ideas.

We address the possibility that the differential use of synonyms or buzzwords by young scientists might drive the results in two ways. First, we manually investigate the list of popular ideas inputs in each year and remove synonyms for old ideas. We conduct a sensitivity analysis with this edited list to test whether our main results change as a consequence. Second, if differential use of buzzwords are driving our results, we would expect groups of early-career scientists working alone – in the absence of more experienced scientists – to be the most likely to use newer words. We explicitly test whether this is the case.

Based on the age of the *newest* idea input of each paper, we construct an indicator variable that captures whether a paper builds on relatively recent ideas. Our main outcome is an indicator variable that captures which publications are among the top 20% based on how recent is the newest idea input in each paper. In additional analyses, we confirm that the results are robust to choosing a different cutoff percentile or a more restrictive comparison set than papers published in the same year.

For our primary results, we construct the idea input age measure for each paper based on mentions of the 100 ideas of each idea "cohort" that were mentioned the most often in publications by the end of the sample period (the cohort of an idea is the year that the idea first appears in the data). The focus on the top 100 ideas in each idea cohort centers attention on the early adoption of new ideas that are the best (on average). Arguably, it is most valuable to

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focus of our paper. As a robustness check, we perform the analyses also when idea mentions are ignored for the first year that the idea appears in the database.

[4] The same approach has been applied to patents to uncover idea inputs in technological innovation (Packalen and Bhattacharya, 2012). Citations are an alternative approach to measure idea inputs (e.g. Jones et al, 2014) but are ill-suited for the present application. A citation to a recent publication does not necessarily indicate that a new idea is being tried out; it may reflect mere similarity of research goals rather than the trying out of an idea in the cited publication. Younger and older researchers have also different incentives to cite recent work, making comparisons of citation ages across authors at different career stages uninformative (Gingras et al, 2008).

ascertain which author characteristics promote the trying out of the best new ideas. But we also conduct sensitivity analyses based on mentions of the top 1,000 and the top 10,000 ideas in each idea cohort, thus revealing also to what extent the results extend to the trying out of new ideas in general.

We define the career stage of each researcher as the number of years that has passed since the author's first publication in MEDLINE. While we do not determine the physical age of a researcher, we can accurately determine the career-stage of each author for articles published 1980-2008. Others have suggested that career age is a more important driver of research productivity than physical age (Simonton, 1997).

To avoid the problem of two or more authors with the same name, we use a validated "Author-ity" MEDLINE author disambiguation database designed exactly for this purpose (Torvik and Smalheiser, 2009; Torvik et al., 2005). As a robustness check, we confirm the results using a simpler disambiguation approach that limits the analysis to authors with an unusual last name and initials combination (see *Web Appendix*). The disambiguation data cover articles in MEDLINE through 2008. Because comprehensive MEDLINE coverage begins in 1946, career stage is much less accurately determined for articles published before 1980. We thus limit the analyses to articles published in years 1980-2008. The vintage of each idea input is, however, determined based on the text of all publications in MEDLINE.

Further details on the data and methods are provided in the *Web Appendix.*

3. RESULTS

We start the presentation of our results by showing for all papers – both team and solo authored papers – how the probability of referencing the most recently introduced ideas varies by the career age of the authors. Later in this section, we explicitly consider how teamwork and team composition affects the probability of trying out new ideas. Figure 1 plots the relationship between author career age and the share of papers that built on new ideas.

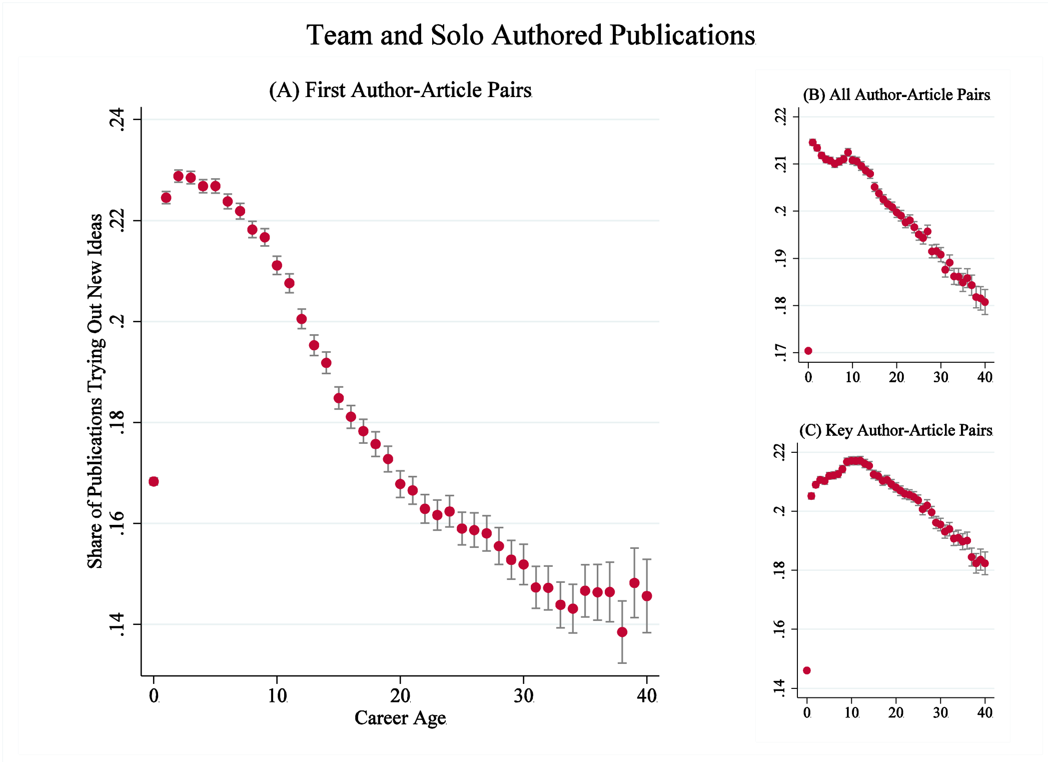

Figure 1. Relationship between career age and the trying out of new ideas in all research articles (team and solo authored). Panels capture first author-article pairs (A; N=6,421,082); all author-article pairs (B; N=28,808,579), and key author-article pairs (B; N=12,205,850). In each panel, the vertical axis depicts the share of publications that are among the top 20% based on how recent is the newest idea input in each paper. The horizontal axis depicts the career age of an author. Capped lines indicate 95% confidence intervals.

The most striking finding in Figure 1 is that the probability of trying out a new idea is at its maximum only a small number of years after an author's first published paper. After that, the probability of trying out new ideas declines steadily. In the main panel, only the first author-article pairs are considered. The right panels of Figure 1 extend the analysis to all author-article pairs and to key author (first or last author)-article pairs. Across all three approaches we find the same main result: the probability of trying out new ideas declines with career age after the early stage of a career. We should note that the figure does not imply that only younger scientists try out novel ideas; according to the figure even late career scientists have a substantial, though significantly lesser, probability of trying out such ideas.

Regression analyses demonstrate that the results we show in Figure 1 are qualitatively and quantitatively robust to a wide variety of assumptions about the construction of the data, author disambiguation, years of analysis, the set of idea inputs that are considered, the way the novelty of idea inputs is calculated, and construction of comparison groups (*Web Appendix*, Tables S2-S6). For instance, we find that our results are confirmed even when we condition on research area or on journal (Table S6). That is, in comparing two papers published in the same research field in the same year, one published by an earlier career first author is substantially more likely to try out newer ideas. Similarly, in comparing two papers published in the same journal in the same year, the paper by an earlier career first author is more likely to try out newer ideas. Our analyses also address the possibility that younger researchers 'jumping on a promising wagon' drive the results. First, we calculate the age of idea inputs based on mentions of those new ideas that later become the most popular idea inputs. Thus, our analysis centers on ideas that have stood the test of time rather than ideas that were quickly forgotten. Second, we conducted additional analyses in which for each new concept we only consider the 50 first mentions of that idea and ignore all later mentions (Table S5). Thus, bandwagon effects do not drive our results.

Some evidence suggests that the first author of biomedical papers plays a key role in generating the ideas and doing the bulk of the work, the last author also often contributes in those ways as well (Shapiro et al., 1994; Baerlocher et al., 2007; Bhandari et al, 2004; Zbar and Frank, 2011). For our purposes here, we need take no position about which author contributed most: our findings across the panels in Figure 1 suggests that more experienced researchers tend to be engaged in projects that are less likely try out newer ideas.

For single-authored papers too, the probability of trying the most novel ideas declines with career age over the bulk of a career (*Web Appendix*, Figure S1). However, solo authored papers, as a whole, are less likely to try out novel ideas than multi-authored papers. Furthermore, the probability of trying out novel ideas increases during the first ten to fifteen career years. One interpretation of this finding is that early career scientists need mentorship and support from others when they try out new ideas. We return to this issue below.

The decline in trying out new ideas with career age of the first authors holds for coauthored papers as well (*Web Appendix*, Figure S2). One possible explanation for this pattern may be that earlier career authors seek out more collaboration, resulting in papers with more novel ideas. We test this explanation by comparing early and late career first authors in papers with the same number of coauthors (*Web Appendix*, panel B of Figure S2). We find that this decline in tolerance for novelty with career age persists when comparisons are only performed across papers with the same number of authors.

Of course, the age of the first author is not the only factor contributing to a propensity to try out new ideas, but other factors, such as team size and the career stage of collaborators may matter as well. We turn to these issues next.

In Figure 2, we address the relationship between the number of authors on a paper and the likelihood of trying out the newest ideas. *A priori*, two distinct stories are possible. In one, each additional author may bring an additional chance for the project to consider a novel idea. Alternatively, group pressures may limit the willingness or incentives of individual scientists to advocate for new approaches (Olson, 1965; Donald et al., 1958). It is an empirical matter to check which story holds up best in the data.

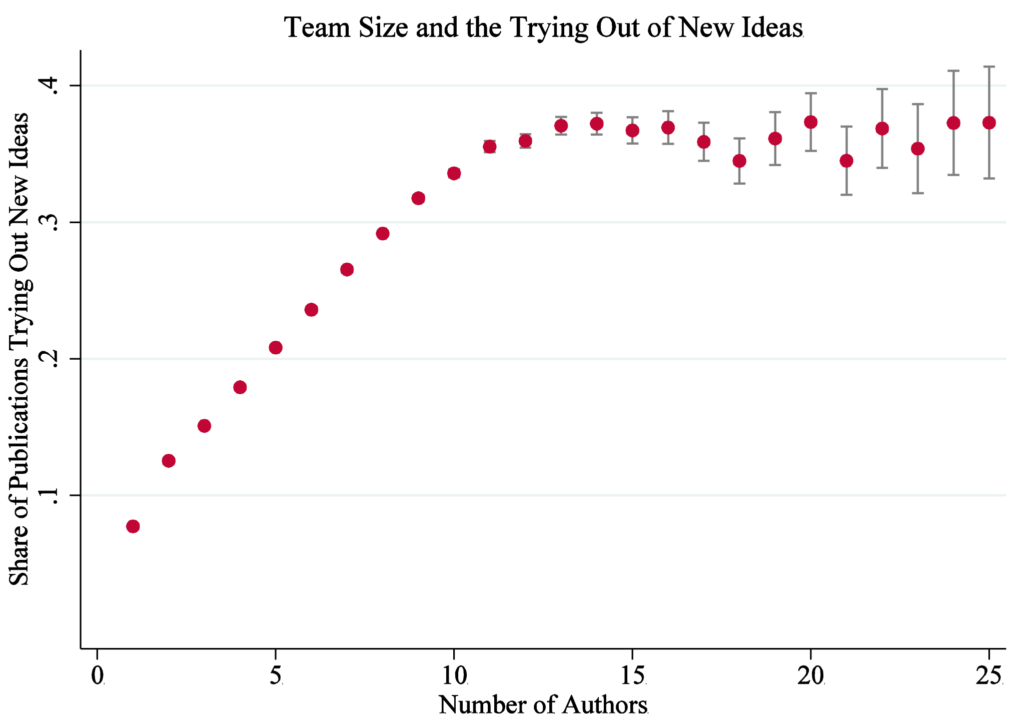

Figure 2. Relationship between the number of authors and the trying out of new ideas (N=3,805,907). The vertical axis depicts the share of publications that are among the top 20% based on how recent is the newest idea input in each paper. The horizontal axis depicts the number of authors. Capped lines indicate 95% confidence intervals.

Strikingly, each additional author increases the probability of referencing the newest ideas (Figure 2). Even adding a 9th or 10th author to a paper does not reduce this probability. These results are robust to adjusting for the ages of the key authors (*Web Appendix*, Figure S3). It is possible to make too much of these findings – perhaps a project is more likely to attract middle authors if it successfully tries out the newest ideas. Nevertheless, it is clear that collaboration is not inherently destructive to the adoption of the newest ideas.

In addition to the number of coauthors, the characteristics of the coauthors may matter as well. We are particularly interested in interactions that take place between the first author and last author of an article – stereotypically the authors who contribute most to the ideas in a biomedical research paper (Shapiro et al., 1994; Baerlocher et al., 2007; Bhandari et al, 2004; Zbar and Frank, 2011). Perhaps, to try out new ideas in a paper, there needs to be both a young scientist who is attuned to the novel ideas in the air, and a more experienced scientist who provides wisdom about whether the novel ideas are worth trying out. Alternatively, the presence of a late-career scientist on a project may discourage the use of the newest ideas.

In Figure 3 we present an analysis of how differing combinations of first author and last author experience contribute to trying out new ideas in a paper. The axes plot the career ages of the first and last author. We color each square of the grid according to the probability that the particular combination of author ages have of trying out new ideas (red is more likely, blue less).

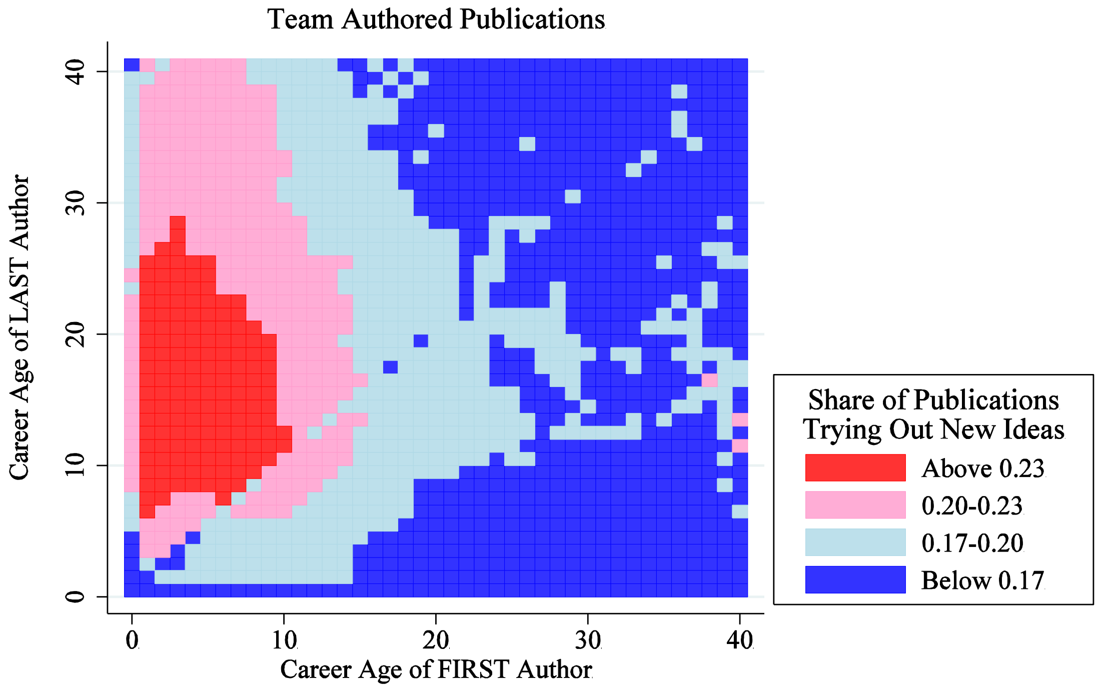

Figure 3. Relationship between career ages and the trying out of new ideas among team authored publications (N=5,785,239). The vertical axis depicts the career age of the last author. The horizontal axis depicts the career age of the first author. Colors capture the share of publications that are among the top 20% based on how recent is the newest idea input in each paper. To calculate the top 20% status, each paper is compared to other papers that were published in the same year and have the same number of authors.

To us, the most striking finding in Figure 3 is that the career age of the first author plays the most important role in determining the tolerance for novelty. If the first author is in the first decade of his or her career, the chance of a paper trying out newer ideas is greatest nearly regardless of the career age of the last author (nearly all the dark and light red cells in Figure 3 are on the left side of the graph). Conversely, having a seasoned scientist as the last author does not prevent a high probability of trying out new ideas as long, as the first author is an early career scientist.

There are three important exceptions to the generalization that younger first authors are more likely to tolerate novelty. First, papers published by scientists who are at the very beginning of their career (left-most vertical line in the grid in Figure 3) are not as likely as other early career scientists to incorporate novelty – even if they are working with more senior scientists. This finding persists if we exclude authors with just one publication (*Web Appendix*, Figure S4).

Second, a team consisting of a young first author and a young last author (the bottom left of the grid in Figure 3) is less likely to try out novel ideas. For this team configuration, holding fixed the experience of the first author, papers are more likely to try out the newest ideas as the last author becomes more experienced.

Finally, if a young first author is paired with a very experienced senior author (the top left of the grid in Figure 3), the papers produced appear to be less likely to try out novel ideas than papers produced by a team with a mid-career senior author and a young lead author.

Regression analyses confirm that these patterns are robust to a variety of ways of constructing the sample, comparison groups, and unobserved control variables (*Web Appendix*, Table S7). These results show that mid-career authors working together with younger authors is a setting in which the trying out of new ideas is most likely. Further regression analyses consider the career ages of the first, last, and also the second author; team combinations that are the most likely to try out new ideas again have a young first author and an experienced last author, confirming the first and last authors as the key authors (*Web Appendix*, Table S8).

One additional implication of Figure 3 is that the novel terms used by young authors are not simply an idiosyncratic novelty due to relabeling of old ideas with new words. First, even when paired with older authors – who presumably know the standard terms when they exist – younger authors are more likely to try out the newest ideas. Second, when young first authors are paired with young last authors, they are *less* likely to try out new terms. Third, when we reanalyze our results using a list of popular novel ideas that have been manually edited to explicitly remove synonyms for old ideas, we find essentially the same pattern of results that we report in the figures above (*Web Appendix*, Table S4). Finally, the list of popular new ideas contains ideas that most knowledgeable experts would recognize as novel for their time rather than a repackaging of old ideas. We include the complete list of ideas in the *Web Appendix* (Table S1) so the reader can make an independent judgment. It is thus unlikely that the appearance of the new terms reflects simply a preference for novel synonyms or buzzwords rather than the trying out of new ideas.

4. CONCLUSION

It is an important goal of wise science policy to identify factors that are conducive to the trying out of new ideas, and to move policy levers that promote innovative experimentation. Ideas when they are first born are necessarily raw and in need of revision and attention by many others (Kuhn, 1962, 1977; Usher , 1929). Scientific progress thus depends on scientists being willing to try out new ideas.

Our primary finding is that papers published by scientists earlier in their career are (on average) more likely to try out newer ideas than papers published by more seasoned scientists. So perhaps Charles Darwin and Max Planck were right: younger scientists are more tolerant of novelty in their work. However, we do not believe that our results imply that, as Planck once wrote, that science advances one obituary at a time. Instead, we find an important role played by later-career scientists.

Our results reinforce the importance of mentorship and teamwork in the adoption and trying out of new ideas in biomedical science. Papers published by teams of younger scientists (as first authors) and mid-career and older scientists (as last author), are more likely to reference newer ideas than papers published alone by young scientists. The stereotypical model of a successful scientific team envisions a brash, young scientist – brimming with untested insights – paired together with the wiser, older scientist with the judgment to help guide and encourage the young scientist. Our findings suggest that this model team is indeed fruitful for scientific progress, at least in terms of trying out and playing around with new ideas.

Our findings have some important implications for science policy. For instance, the National Institutes of Health (NIH) in the United States explicitly gives early career scientists an advantage in their application for grant funding. Early career applicants are not required to meet the same standards regarding past productivity in their evaluation by NIH scientific review panels. This policy is usually justified as an investment in the future – the NIH should be more willing to fund early career scientists who are less productive to date than older scientists as a way to help young scientists develop and mature. In this reasoning, there is a trade-off between funding highly productive grant applications now and less productive grant applications that will result in a better-trained scientific workforce in the future. Our findings suggest that a preference for early career scientists might have an additional benefit in terms of scientific productivity, at least in terms of funding those scientists who are most likely to seek out novel ideas for their work.

Finally, our findings suggest a re-evaluation of the traditional case made for universities providing guaranteed tenure to research scientists. Typically, the argument made for tenure is that it frees scientists from the risks associated with failure from exploring a new or controversial insight. Since after tenure, scientist's job security is not tied to the success or failure of their research program, the argument goes, they should be more willing to try out risky ideas in their work. We find no support for this traditional argument in the data. To the extent that senior scientists (on average) are more willing to work with new ideas, it is only in collaboration with younger, often untenured, scientists. Of course, there may still be a case to be made for tenure that is based on the productive role played by senior scientists in encouraging novel scientific exploration by their junior colleagues, as well as other arguments such as the freedom to teach without fear of censorship. A full evaluation of the costs and benefits of tenure is needed before it is time to rethink tenure altogether.

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Web Appendix: Methods and Materials

A.1 Data Sources

Our main data source is the MEDLINE database. These data can be downloaded by anyone (http://www.nlm.nih.gov/bsd/licensee/medpmmenu.html); the required license agreement is free. MEDLINE is U.S. National Library of Medicine's indexed database on over 20 million published biomedical journal articles. MEDLINE mainly covers nearly all biomedical research articles published 1946-present but also some older papers are included. The database lists the title, authors, and journal of each article and also the abstract for articles published since 1975. We use the data available for download in November 2012, which cover years 1946-2011.

Our secondary data source is the "Author-ity" MEDLINE author disambiguation database (*1*, *2*). This data source allows us to resolve the identity of scientists with the same name, even in years before unique author ids were assigned. The 2006 version can be downloaded for non-profit academic use by anyone (http://arrowsmith.psych.uic.edu/arrowsmith_uic/author2.html); the required license agreement is free. We used the 2008 version of the database. The main results can be closely replicated also without access to the Author-ity database by relying on an alternative MEDLINE author disambiguation approach. Both MEDLINE author disambiguations are described below in Section A.4.

In defining research areas further below, we refer to the Medical Subject Headings ("MESH") controlled vocabulary. The vocabulary can be browsed and downloaded at https://www.nlm.nih .gov/mesh/.

A.2 Indexing Idea Inputs

As discussed in the main text, we capture idea inputs from the text of the research articles. For each article, we index all words and all 2- and 3-word sequences that appear in the available text (title and abstract). Before this indexing, we do the following preparations:

1. We render all alphabetic characters lower-case characters.
2. We eliminate the possessive case by eliminating the character sequence " 's " and by replacing the character sequence " s' " with " s ".
3. We eliminate non-alphabetic and non-numeric characters.
4. We eliminate the 313 common words that appear in the list of common words available at http://mbr.nlm.nih.gov/Download/2009/WordCounts/wrd_stop; this stop word list is provided by the National Library of Medicine, which also provides the MEDLINE data. Eliminating these very common words mainly limits the storage requirements for the rest of the indexing analyses.

5. We eliminate words that are fewer than 3 characters long.

6. We eliminate words that are gene sequences.

7. We eliminate words that include any of the following character sequences: “web”, “www”, “http”, “pubmed”, “medline”.

8. We eliminate all words that have two or more consecutive numbers.

Words on opposite sides of an eliminated word are not indexed in the list of word sequences that appear. Similarly, words that are separated by a comma, a period, a colon, or a semi-colon, and a subsequent empty space, are not indexed in the list of word sequences.

We index all words that are 3-29 characters long, all 2-word sequences that are 7-59 characters long, and all 3-word sequences that are 11-89 characters long. We refer to these words and word sequences as *concepts*.

The analysis reveals the year of the first appearance of each concept, which we refer to as the concept's *cohort*. The analysis also reveals which publications mention each concept as well as in how many publications each concept appears. We use the cohort years and concept mentions to determine the vintage of idea inputs in each publication (see the main text or further below). We focus the main analysis on mentions of the top 100 concepts in each cohort, with concept rank determined based on the number of MEDLINE publications in which the concept appears. This allows is to examine which author characteristics promote the trying out of the ideas that are the best (on average). In sensitivity analyses, we extend the analysis to the top 1,000 and the top 10,000 concepts in each cohort.

We now show the reader the list all the top 100 concepts in concept cohorts 1960 through 2008. These are the cohorts based on which we calculate the age of the newest idea input for each paper. In line with the goals of our paper, the order of concepts in this list reflects the number of times each concept's appearance renders a paper a top 20% paper in terms of the age of its idea inputs. To order the concepts in this way in the list, we first determine for each concept the set of papers in which concept is the newest top 100 concept that appears in the paper, and then count how many of the papers in that set have the top 20% status in terms of the age of the newest idea input (the comparison group for a given paper is all other papers published in the same year). When two or more concepts share the distinction of being the newest top 100 concept in a paper, we only count the appearance of the longest such concept. For instance, when a paper mentions concepts “polymerase chain”, “pcr amplification” and “polymerase chain reaction” from the 1986 cohort, for the purposes of ordering the concepts in the list we only count the appearance of the concept “polymerase chain reaction”.

Table S1: List of idea inputs identified by our approach. Please click here for an *embedded* list of the top 100 concepts in cohorts for years 1960-2008 (the list is also available separately online because submission system may not process embedded files correctly; the link is an internal link which opens an embedded PDF file and does not access the internet; the link works inside Adobe Acrobat – it may not open inside a browser).

In the embedded list, columns 1-3 list:

1. Concept name.

2. Cohort of the concept (the year of first appearance of the concept in the MEDLINE data).

3. Number of times the concept is the newest concept in a paper that has the top 20% status based on the age of the newest idea input in the paper.

As the reader can readily verify by looking at this list – especially a reader with some familiarity with biomedicine – the concepts revealed by this indexing effort mostly represent ideas that are known to have been important new idea inputs in biomedicine in recent decades.

While overall our approach is very successful, some of the concepts in the list do not reflect idea inputs. We have manually examined the list to find such concepts as well as concepts which reflect idea inputs but are assigned to a cohort that is obviously wrong (the latter happens most often when an acronym gets a new meaning – examples include "pcr" and "hiv"). In the embedded list we have marked such suspect concepts with the label "exclude in sensitivity analysis" in column 4. The suspect concepts are mostly common words and word sequences (an example is the concept "results demonstrated" in cohort 1966), and account for 11% of all the concepts in the list. Moreover, because most of the suspect concepts are in the 1960s and 1970s cohorts, the suspect concepts are rarely the newest concept in a paper. Consequently, the suspect concepts account for less than 2% of the times that a concept in this list renders a paper the top 20% status based on the age of the newest idea input (this less than 2% figure is calculated based on the numbers in column 3 of the embedded list). It is thus unsurprising that when we conduct a sensitivity analysis in which we ignore mentions concepts that are marked with the label "exclude in sensitivity analysis" in the embedded list, the results are very similar to the results that we obtain when all concepts in the embedded list are considered (the results from this sensitivity analysis are reported further below in column 6 of Table S4).

In the concept list there are some instances where both plural and singular forms of a word are found on the list (for example, "retrovirus" and "retroviruses" in cohort 1976). Our view is that these usages reflect distinct though related ideas, and we treat them as such in our analysis. In this instance, the move from considering one virus to considering multiple viruses involves a broader research perspective. Moreover, the singular and plural forms appear typically in the same or adjacent cohorts. A sensitivity analysis that involved removing plural forms would thus produce very similar results as the ones we report.

Finally, in the list there are many instances when subsets of a phrase will appear on our list along with the entire phrase itself. For instance, "polymerase chain" and "polymerase chain reaction" appear in cohort 1986. Because such concept pairs typically have the same cohort year, removing all these subsets from our lists would also change our results very little.

A.3 Sample Construction

While we determine (1) the cohort of a concept based on the year of its first appearance in any publication in the data, and (2) the rank of each concept within its cohort based on the number of times the concept appears in all the publications in the data, we limit the rest of the analysis to publications for which the available information on the title and abstract contains at least 30 words in total. For the excluded publications the data likely have too little information on their idea inputs.

We also restrict the analysis to regular journal articles, thereby excluding comments, editorials, case reports, etc. We achieve this we exclude articles that are not indexed with the MESH "Publication Type" term "Journal Article" and further restrict the sample by excluding articles that are indexed with any of the MESH "Publication Type" terms "Review", "English Abstract", "Case Reports","Historical Article" or "Comment", "Portrait" or have a MESH "Publication Type" term with any of the character sequences "biography", "Biography", "guideline", "Guideline", "News", or "Conference" in them (capturing multiple additional publication types that are not regular research articles). The rationale to limiting to regular journal articles is that older researchers can be expected to publish editorials and comments in addition to regular research articles, and including such articles in the analysis might bias the findings against older scholars.

A.4 Author Disambiguation

The quality of an author disambiguation can be measured by the extent of splitting and lumping. Splitting refers to the extent to which articles written by the same real author are incorrectly assigned to different author clusters. Lumping refers to the extent to which articles written by different real world authors are incorrectly assigned to the same author cluster. Overall, the quality of the Author-ity MEDLINE author disambiguation has been found high on both dimensions: only 2% of articles are affected by splitting and less than 0.5% of clusters are affected by lumping (*2*).

In spite of its high quality, the Author-ity disambiguation has a potential drawback in terms of our research goals, one that stems mainly from its use of information on research topics as one of the many factors that determine whether two articles are by the same author. Specifically, in the Author-ity disambiguation, the MESH terms that are indexed to a given MEDLINE article are compared to the MESH terms indexed to another MEDLINE article to help determine whether the two articles are by the same author. Two articles with very different MESH terms are deemed less likely to be by the same author than two articles with similar MESH terms. Even though we do not measure novelty from MESH headings but instead measure novelty from the text of an article's title and abstract, this aspect of the Author-ity disambiguation introduces the possibility that when an experienced researcher publishes a paper that builds on a new idea, the article is less likely to be deemed to belong to the same experienced author compared to an article by the same author that does not build on a new idea. This occurs if MESH headings are systematically different for papers that build on new ideas than MESH headings for papers that build on well-established ideas. To the extent that this does occur, one would find a spurious relationship between researcher career age and novelty of idea inputs (as novel papers by experienced researchers are erroneously assigned to fictitious early-career researchers).

We address this potential drawback in two ways. First, we conduct analyses in which we control for MESH headings by constructing comparison groups for papers based on the MESH terms indexed to the papers (Table S6 below). Second, and more importantly, we construct an alternative MEDLINE author disambiguation that does not use any other information than researcher name to disambiguate authors in MEDLINE. For any systematic bias to remain, one would have to believe that changes in real names of researchers are correlated with changes in research topics (say, researchers who change their last name upon marriage are more to change their research topics than are other experienced researchers) and that such a factor is quantitatively important (given the large size of our estimated effects).

To construct the alternative disambiguation, we first determine the last name, first name, middle initials and suffix combination for each author-article pair. We then exclude all last name-initials-suffix combinations which are matched to more than one full first name (author's full first name is included mostly only for papers published 2002 or later). We also exclude last name-initials-suffix combinations that are matched to more than 50 papers in any single year. The results for the alternative author disambiguation are reported in Tables S3 and S7; the two disambiguation approaches yield qualitively and quantitatively very similar results.

A.5 Construction of Outcome Measures

In this section, we provide a more detailed discussion of the construction of variables measuring the age of idea inputs. Please recall that our main goal is to generate a measure of the age of the ideas referenced in each paper based upon the text available to us in the MEDLINE database. Recall also, that we define a concept as a sequence of one-, two-, or three- words occurring next to each other in a MEDLINE entry for a particular article. In what follows, we will index each publication in MEDLINE with two numbers – i references a unique publication identifier for each paper published in year t.

A.5.1 Determining the cohort and age of each concept

Consider a concept k referenced in paper (i, t). While it is possible that concept k was first introduced in paper (i, t), it is more likely that the same concept (word or word combination) can be found in papers published earlier. For each concept, we calculate cohort(k) as the calendar year the concept was first mentioned in all the publications in the MEDLINE database. For the earliest years, this function will be a noisy measure of novelty. Even common words and word sequences, such as "different pattern" and "contextual", have a first occurrence in MEDLINE. However, given the large number of publications in each year, the error from common words will decline over time. Because of this feature of the way we define the age of ideas, we report information starting in the decades after a "burn-in" period, after which most of the common words have already had their first appearance. In particular, in our main regression analysis, we use concepts from the cohort 1960 onward to index the idea inputs of each paper, even though the comprehensive MEDLINE coverage of biomedical publications starts in 1946.

For any concept k, we define the concept's age at year t, denoted $age_t(k)$, as the number of years as of year t since concept k was introduced into the biomedical literature. Thus, $age_t(k) = t - \text{cohort}(k)$.

A.5.2 Determining top concepts in each cohort

Our next step is to identify the list of top concepts newly introduced into the biomedical literature in each year. That is, for each year t we must rank concepts k for which cohort$(k) = t$.

To do this, for each concept k with a given cohort(k) we calculate the total number of MEDLINE publications in which the concept k is referenced from the year cohort(k) through to the end of the sample (year 2011). Thus, we define whether a concept is a top concept based on how many publications the concept appears in. By focusing on a list of top new concepts, we focus the analysis on the best new concepts (see the main text) and also eliminate problems introduced by papers with typographic errors, non-standard locutions, and other such novel textual material which do not actually constitute novel ideas. To test the sensitivity of our results to the length of the list of concepts we track, we estimate the regression models separately using the lists of top 100 concepts, top 1,000, and top 10,000 concepts in each concept cohort. The main results that we present in the paper focus on the list of the top 100 concepts in each concept cohort.

A.5.3 Determining whether paper tries out a new idea

Finally, we categorize each paper in the MEDLINE data by creating an indicator variable for whether it among the papers published in that year that reference the newest ideas. To make this definition clear, let $M_{i,t}$ be the set of top 100 concepts referenced in paper (i, t) so that $k \in M_{i,t}$ if and only if concept k appears in publication (i, t) and concept k is found on a top 100 list of concepts (defined above).

With the appearances of top 100 concepts indexed for each paper, and represented by the set $M_{i,t}$, let $minM_{i,t} = min(age(M_{i,t}))$ be the minimum over the ages of the top 100 concepts that appear in the article (i, t). We refer to $minM_{i,t}$ as the age of the idea inputs that are referenced in paper (i, t); it is a basic building block for our analysis.

Next, let $M_t = \{minM_{1,t}, minM_{2,t}, ...\}$ be a list of concept ages of all the articles published in year t. Let $\#\{M_t\}$ be the number of elements in M_t (which equals the number of papers published in year t) and let $\#\{M_t|A\}$ the number of elements of M_t for which some condition A is true.

Finally, let $F_t(z) = P(minM_{i,t} \leq z) = \#\{M_t|M_t \leq z\}/\#\{M_t\}$ be the cumulative density function of $M_{i,t}$ over the set of articles published in year t.

We define $z20_t$ to be the 20th percentile of the M_t distribution. Thus, $F_t(z20_t) = 0.2$. Papers with $minM_{i,t} \leq z20_t$ thus, by definition, reference a concept that place the paper among the most novel of the papers published in that year. We define an indicator variable, $d20_{i,t}$, which equals one if the paper is in the top 20th percentile that year by the recency of the ideas it references (that is, it satisfies $minM_{i,t} \leq z20_t$) and equals zero otherwise. In a sensitivity analysis, we define similar measure, $d05_{i,t}$, for the 5th percentile of papers.

A.6 Analyses

We perform two sets of analyses: non-parametric analyses (reported in the main text) and parametric regression analyses (reported below). To test the sensitivity of our results to the assumptions we have made in constructing the data, we need a statistical method that provides an easy way to compare the results as we vary our assumptions. The non-parametric method is attractive because it generates visually striking graphs, but it does not permit a simple comparison across model results that pertain under different assumptions. To this end, we conduct our sensitivity analyses by estimating flexible parametric regression models instead, since these do permit simple comparisons of analysis results under different sets of assumptions.

A.6.1 Non-parametric analyses (reported in the main text)

In the non-parametric analyses reported in Figures 1, S1 and S2 we calculate the mean of the outcome variable, and the associated 95% confidence interval, separately for each career age.

In calculating the mean of the outcome variable for a given career age, the observations are weighted so that the total weight of observations from any given year is the same as the total weight of observations from any other year (1980 through 2008). This way, the results are not driven by observations on the most recent years (the data contain more observations for the more recent years).

We limit the analysis to career ages 0-40 for two reasons: (1) the comprehensive coverage of the data do not begin until 1946 and thus career ages older than 40 are not reliably determined for 1980s, and (2) the lower number of research papers by researchers with career ages older than 40 implies that any obtained estimates involve considerably more uncertainty. We exclude observations for which the comparison group includes fewer than 5 observations (a small number of articles makes the variable capturing which articles are in the top 20% newest based on age of idea inputs less informative). As discussed in the main text, we limit the analysis to years 1980-2008. In calculating the weighted mean for a given career age, we exclude observations on years for which there are fewer than 200 observations (analyses with team authored papers) or fewer than 20 observations (analyses with only solo authored papers). Throughout the analyses, non-parametric and parametric, we drop observations in comparison groups with less than five observations (the outcome variable – typically, the top 20% status in terms of newness of idea inputs – is calculated relative to other articles in the comparison group).

The panels in Figure 1 were created based on 6,421,082 first author-article pairs (main panel), on 28,808,579 any author-article pairs (upper right panel), and on 12,205,850 key author (first or last author)-article pairs (lower right panel). For the analyses in the right panels, each author-article pair is treated as a separate contribution. Figure S1 (shown below) was created based on 436,784 lone author-

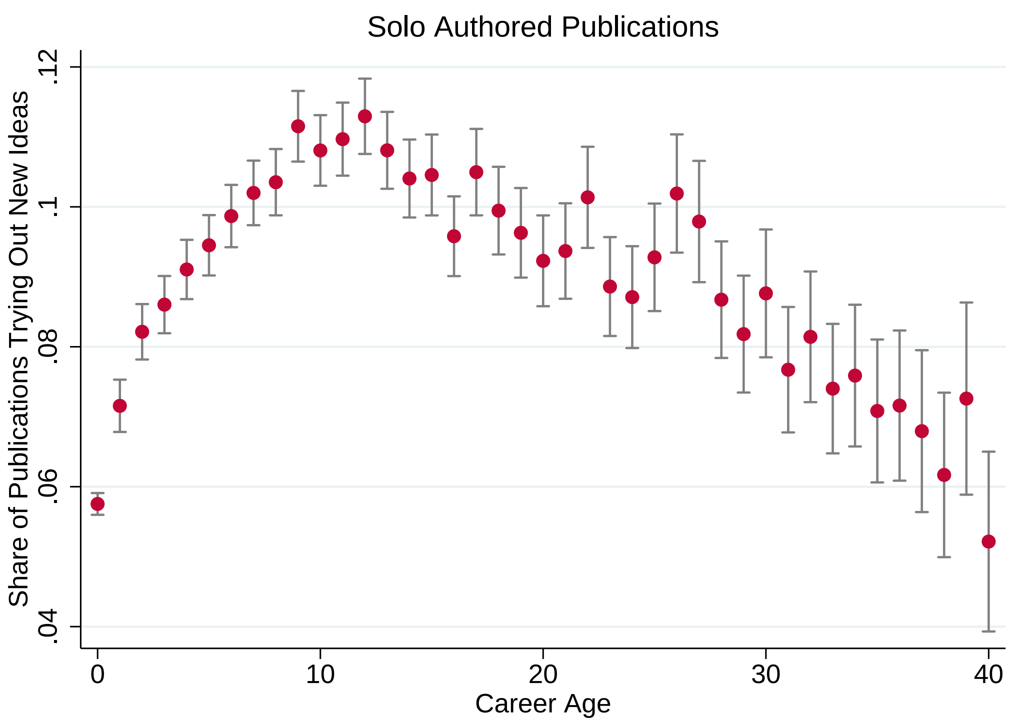

Figure S1: Relationship between career age and the trying out of new ideas among solo authored publications (N=436,784). The vertical axis depicts the share of publications that are among the top 20% newest based on the age of the newest idea input. Capped lines indicate 95% confidence intervals.

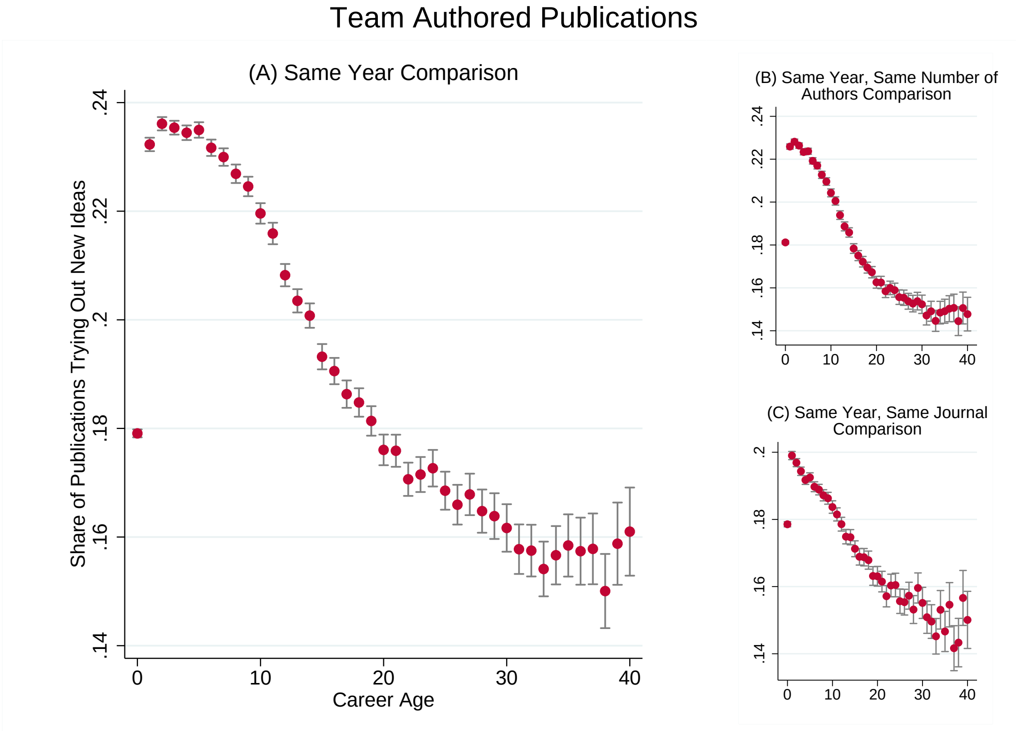

Figure S2: Relationship between career age and the trying out of new ideas among team authored publications. The vertical axis depicts the share of publications that are among the top 20% newest based on the age of the newest idea input. The horizontal axis depicts the first author's career age. In main panel (A; N=5,983,958) the comparison group for determining the top 20% status is articles published in the same year. In panel B (N=5,982,385) the comparison group is articles that are published in the same year and have the same number of authors. In panel C (N=5,414,544) the comparison group is articles that are published in the same year in the same journal and have also the same number of authors. Capped lines indicate 95% confidence intervals.

article pairs. Papers with just one author make up only 16% and 4% of the articles published in 1980 and 2008, respectively. The panels in Figure S2 (shown below) were created based on 5,983,958 first author-article pairs (panel A), on 5,982,385 first author-article pairs (panel B), and on 5,414,544 first author-article pairs (panel C).

In the non-parametric analysis reported in Figures 2 and S3 we calculate the mean of the outcome variable and the associated 95% confidence interval, separately for a given number of authors. Analyses in Figures 2 and S3 differ in terms of the comparison group (based on which the outcome variable is calculated). In Figure 2 the comparison group is all articles published in the same year. In panel A of Figure S3 the comparison group is articles that were published in the same year and have the same career age of the first author. In panel B of Figure S3 the articles in the same comparison group have (1) the same publication year, (2) same first author's career age, and (3) same last author's career age.

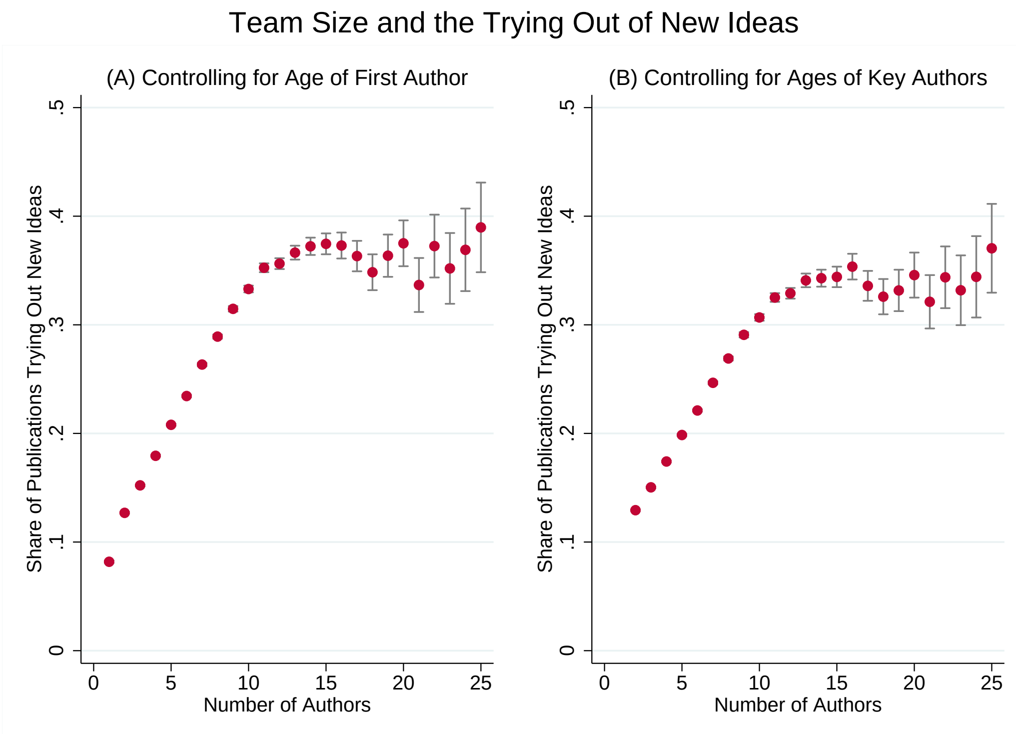

Figure S3: Relationship between the number of authors and the trying out of new ideas, controlling for career age of first author (panel A; N=3,805,907) and career ages of key authors (panel B; N=3,613,338). The vertical axis depicts the share of publications that are among the top 20% newest based on the age of the newest idea input. The horizontal axis depicts the number of authors. In panel (A) the comparison group for determining the top 20% status is articles that were published in the same year and have the same career age of the first author. In panel B the comparison group is articles that are published in the same year and have the same career age of the first author as well as the same career age of the last author. Capped lines indicate 95% confidence intervals.

Figure 2 was created based on 3,805,907 articles. Panels A and B of Figure S3 were created based on 3,805,907 and 3,613,338, articles, respectively. In creating these figure, we exclude observations on years 1980-1995 because for years 1984-1995 the MEDLINE data only includes information the first 10 authors, whereas for 1996-1999 MEDLINE includes information on the first 24 authors and the last author and for 1966-1983 and 2000-present MEDLINE includes information on all authors. We exclude all articles with more than 25 authors. Again, the observations are weighted so that the total weight of observations from any given year is the same as the total weight of observations from any other year.

In the non-parametric analysis reported in Figure 3 we calculate the mean of the outcome variable separately for each combination of the career ages of the first author and the last author. Again, the observations are weighted so that the total weight of observations from any given year is the same as the total weight of observations from any other year (1980 through 2008). Figure 3 was created based on 5,785,239 articles. In creating this figure, we first calculate the weighted mean for each cell (the weighting is as discussed above), and then report a smoothed version of the mean for each cell, where the smoothed mean is constructed by giving the original observation in the cell the weight 1, observations in the cell below, above, on the left, and on the right the weight 0.5, and observations 2 cells below, above, on the left, and on the right the weight 0.25, and observations that touch the corners of the cell the weight 0.25.

Figure S4 repeats the analysis of Figure 3 with one change: here we exclude observations on articles in which either the first or the last author published only one paper during the sample period. Figure S4 was created based on 4,806,902 articles. The result shows that even when we exclude authors with just one publication, papers published by scientists who are at the very beginning of their career (left-most vertical line in the grid in Figures 3 and S4) are not as likely as other early career scientists to build on new ideas (a finding mentioned in the main text).

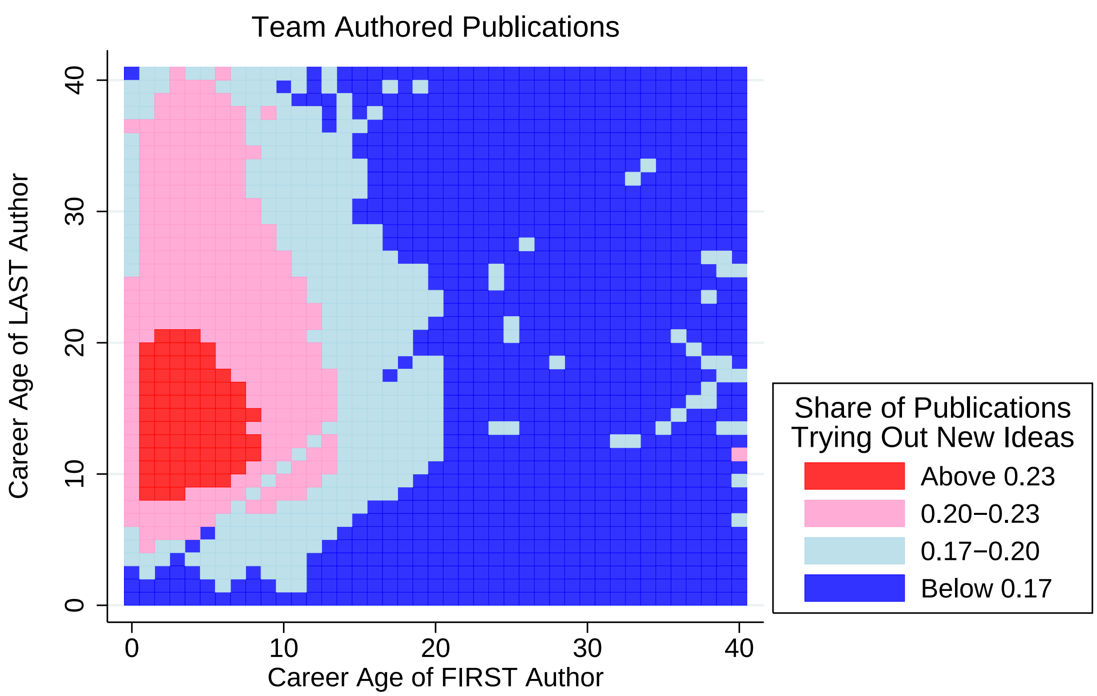

Figure S4: Relationship between career ages and the trying out of new ideas among team authored publications (N=4,806,902). Analysis is the same as in Figure 3 in the main text except here authors with just one publication in the sample are excluded. The vertical axis depicts the career age of the last author. The horizontal axis depicts the career age of the first author. Colors capture the share of publications that are among the top 20% based on how recent is the newest idea input in each paper. To calculate the top 20% status, each paper is compared to other papers that were published in the same year and have the same number of authors.

Figures S5 and S6 in turn repeat the analyses in Figures 1 and 3 with one change: here we use the alternative MEDLINE author disambiguation approach rather than the "Author-ity" disambiguation (Figure 2 does not utilize a disambiguation). Panels A, B, and C of Figure S5 were created based on 3,191,410, 13,616,413, and 6,032,363 observations, respectively. Figure S6 was created based on 1,505,399 observations. As the alternative disambiguation approach likely incorrectly lumps together papers by early-career real authors and papers by later-career real authors more often than does the "Author-ity" approach, it is not surprising that the decline in novelty with age is not quite as steep when the alternative disambiguation is utilized compared to when the "Author-ity" disambiguation is utilized. Yet, comparison of Figure S5 against Figure 1 and Figure S6 against Figure 3 shows that the two disambiguation approaches yield qualitatively and quantitatively similar conclusions (parametric analyses reported below reach the same conclusion; please see Tables S3 and S7).

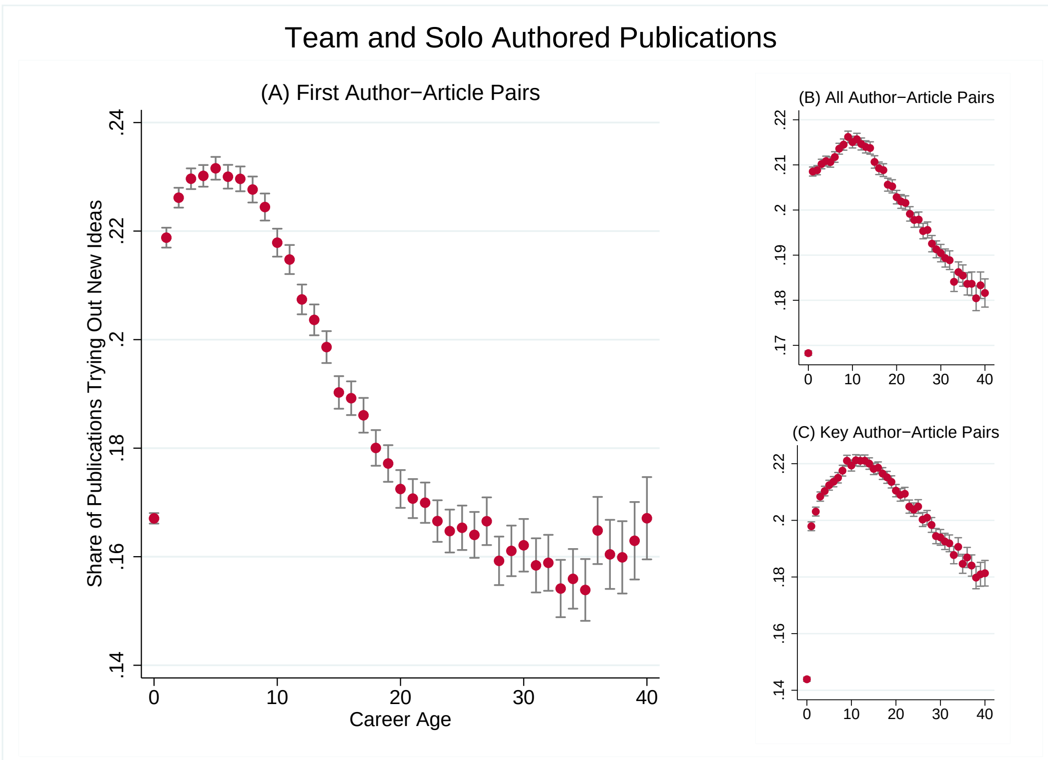

Figure S5: Relationship between career age and the trying out of new ideas in all research articles (team and solo authored). Analysis is the same as in Figure 1 in the main text except the analysis here utilizes the alternative author disambiguation rather than the "Author-ity" disambiguation. Panels capture first author-article pairs (A; N=3,191,410); all author-article pairs (B; N=13,616,413), and key author-article pairs (B; N=6,032,363). In each panel, the vertical axis depicts the share of publications that are among the top 20% based on how recent is the newest idea input in each paper. Capped lines indicate 95% confidence intervals.

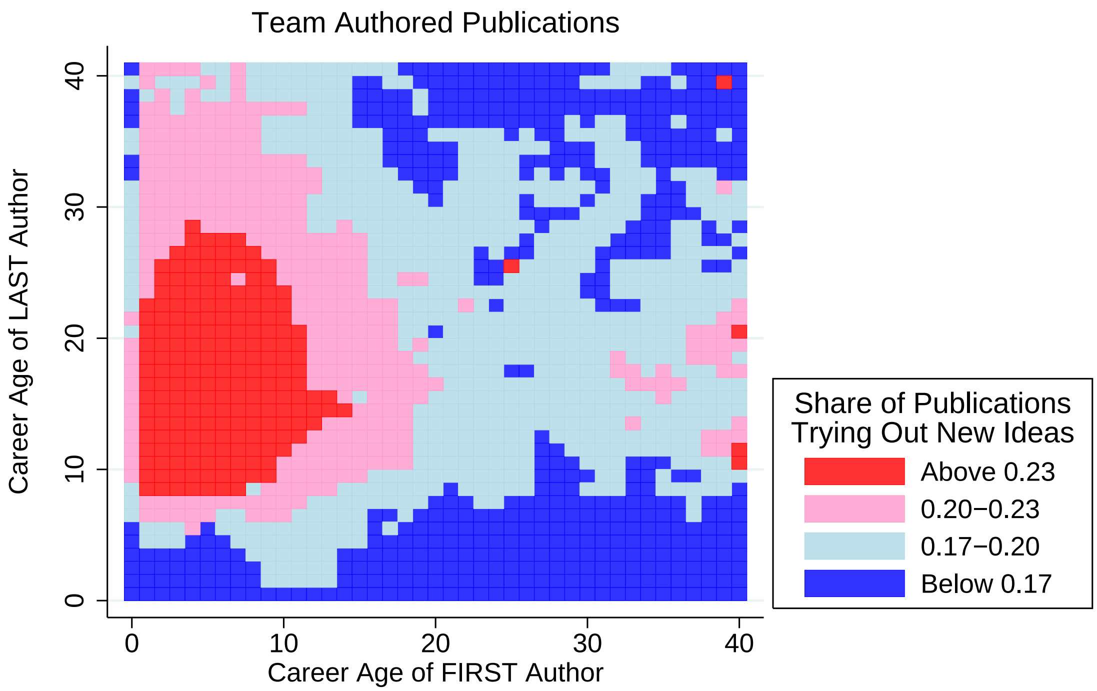

Figure S6: Relationship between career ages and the trying out of new ideas among team authored publications (N=1,505,399). Analysis is the same as in Figure 3 in the main text except the analysis here utilizes the alternative author disambiguation rather than the "Author-ity" disambiguation. The vertical axis depicts the career age of the last author. The horizontal axis depicts the career age of the first author. Colors capture the share of publications that are among the top 20% based on how recent is the newest idea input in each paper. To calculate the top 20% status, each paper is compared to other papers that were published in the same year and have the same number of authors.

A.6.2 Parametric regression analyses

The regression analyses demonstrate that the results we present in the main paper are both qualitatively and quantitatively robust to a wide variety of assumptions about the construction of the data, author disambiguation, years of analysis, the set of idea inputs that are considered, the way novelty of idea inputs is calculated, construction of comparison groups, etc. We employ two alternate regression strategies; one focuses on the career age of authors (Tables S2-S6), while the second focuses on the pairing of authors of different (or similar) career ages (Tables S7-S8). We start our discussion with the first specification in which we regress the outcome variable on the following 5 indicator variables:

- **Career Year 0**, which is 1 for authors with career age 0 (the first year they publish a paper) and 0 otherwise.
- **Career Year 1-10**, which is 1 for authors with career age 1-10 and 0 otherwise.

- **Career Year 11-20**, which is 1 for authors with career age 11-20 and 0 otherwise.
- **Career Year 21-30**, which is 1 for authors with career age 21-30 and 0 otherwise.
- **Career Year 31-40**, which is 1 for authors with career age 31-40 and 0 otherwise.

In reporting the results, we designate the last group **Career Year 31-40** as the omitted group. Results from this specification reveal to which extent our finding in the main text, that the propensity to try out new ideas is much higher for early career researchers than more seasoned researchers, holds across the different sensitivity analyses. The second regression strategy is described further below. To the extent that the finding holds, we would expect that:

1. The coefficient on the dummy variable **Career Year 1-10** is positive, indicating that the propensity to try out new ideas is higher for early career researchers than researchers in the omitted group (late career researchers in career years 31-40).
2. The coefficient on the dummy variable **Career Year 1-10** is higher than both the coefficient on the dummy variable **Career Year 11-20** and the coefficient on the dummy variable **Career Year 21-30**.

In reading the regression tables reported below, the reader should thus examine whether estimates of the coefficients on the dummy variables are positive and exhibit a declining pattern from the coefficient on **Career Year 1-10** to the coefficient on **Career Year 11-20** and from the coefficient on **Career Year 11-20** to the coefficient on **Career Year 21-30**. **The expected pattern indeed emerges across all specifications, which confirms the robustness of the results that we report in the main text to varying assumptions.**

In each estimation, the model also involves a set of Boolean indicator, or dummy, variables, which varies across the analyses; the set of dummy variables employed in each estimation are separately reported with the results. The outcome variable is typically the indicator variable capturing whether the paper is in the top 20% newest based on the age of the newest idea input in the paper. We vary the comparison group used in constructing this variable; the comparison group used in each regression is reported with the results.

As discussed above and in the main text, we vary the set of concepts based on which the outcome variable is calculated from the top 100 concepts in each cohort to the top 1,000 and the top 10,000 concepts; when either of the latter concept sets is employed it is reported with the results. We also employ alternative outcome variables (raw age of the newest idea input in a paper, an indicator variable capturing whether a paper is in the top 5% newest based on the age of the newest idea input, and an indicator variable capturing whether a paper is in the top 50% newest based on the age of the newest idea input; when any of these alternative outcome variables is employed it is reported with the results.

As in the non-parametric analyses, we weight observations so that the total weight of observations from any given year is the same as the total weight of observations from any other year.

Tables S2-S6, shown below, report estimates for the specification mentioned above.

In Table S2 we mainly vary the set of authors considered. In each estimation, the set of dummy variables included is the same as the comparison group that is used to construct the dependent variable.

In columns 1-2 only the first author-article pairs are considered. In column 1 the comparison group is all articles published in the same year by the same number of authors. In column 2 the comparison group is all articles published in the same year.

In column 3 all author-article pairs are considered. In column 4 all key author-article pairs are considered. In both columns the comparison group is all articles published in the same year by the same number of authors.

In column 5 only those first author-article pairs are considered for which the first and last authors are listed a non-alphabetical order. In column 6 only those first author-article pairs are considered for which all authors in the paper are listed the alphabetical order.

In every case, regardless of set of included author-article pairs, we find that that papers produced by authors in career age 1-10 are the most likely to reference newer ideas in their papers, authors in career age 11-20 are second most likely, authors in career age 21-30 third most likely, and authors in career age 31-40 least likely. While the exact differences between these groups vary by specification, qualitatively, this matches the results from the non-parametric analysis that we report in the main text.

In Table S3 we vary the disambiguation used (columns 1-2) and employ author-specific dummy variables (columns 3-5) to examine within career changes.

In column 1 we use the Author-ity MEDLINE author disambiguation. In column 2 we use the alternative MEDLINE author disambiguation we constructed (see Section A.4 above). The advantage of the latter disambiguation approach is that it does not use information on research topics, unlike the Author-ity approach. In both columns the comparison group is articles published in the same year by the same number of authors, the dummy variables correspond to the comparison groups, and only first author-article pairs are considered.

In columns 3-6 we employ a dummy variable for each author, with authors again determined based on the Author-ity disambiguation. In columns 3-4 only first author-article pairs are considered. In column 5 all author-article pairs are considered. In column 6 only key author-article pairs are considered. Analyses in columns 3-4 differ from one another in that in column 3 the comparison group (based on which the outcome variable is calculated) is articles published in the same year by the same number of authors, whereas in column 4 the comparison group is all articles published in the same year. In columns 5 and

6 the comparison group is articles published in the same year by the same number of authors. These "within-career" presented analyses in columns 3-6 form an exception to the rule on how the observations are weighted: for these analyses the observations are weighted so that the total weight of observations for any given author is the same as the total weight of observations for any other author.

In every case, regardless of disambiguation method, included dummy variable set, included sets of author-article pairs, and comparison group we find the same qualitative pattern of age and the probability of trying out new ideas that we report in the main text.

In Table S4 we vary the set of concepts considered in constructing the outcome variable as well as what outcome variable is used. In all cases the comparison group is articles published in the same year by the same number of authors. The set of dummy variables employed correspond to the comparison groups. In all cases only first author-article pairs are considered.

In columns 1-2 we vary the outcome variable. In column 1 the outcome variable is the indicator variable capturing whether the article is among the top 5% newest based on the age of the newest idea input. In column 2 the outcome variable is the raw age of the newest idea input in the article.

In columns 3-4 we vary the set of concepts considered in constructing the outcome variable. The outcome variable is again the indicator variable capturing whether the article is among the top 20% newest based on the age of the newest idea input. In column 3 this variable is constructed based on mentions of top 1,000 concepts in each cohort. In column 4 this variable is constructed based on mentions of top 10,000 concepts in each cohort.

In column 5-6 we again only consider mentions of top 100 concepts in each cohort. The outcome variable is again the indicator variable capturing whether the article is among the top 20% newest based on the age of the newest idea input. In column 5 we ignore mentions of those top 100 concepts that are marked with the label "exclude for sensitivity analysis" in the embedded list (see Section A.2 above). In column 6 we in turn ignore mentions of concepts during the year that the concepts were introduced.

Analyses reported in column 7 too only consider mentions of top 100 concepts in each cohort. For each such concept, we first determine how many MEDLINE articles mention the concept each year and then determine which year the concept was mentioned for the 50th time in the MEDLINE data. We then construct a dummy variable that is 1 for MEDLINE articles that mention any top 100 concept before the concept reached the year of its 50th mention in MEDLINE data (and is 0 otherwise). This dummy variable is used as the outcome variable in the analysis reported in column 7. This approach assigns a paper to be novel only if the paper mentions an idea that is not only important (otherwise the concept is not a top 100 concept) but also has been mentioned in less than 50 papers previously. Consequently, the analysis addresses in part addresses the possibility that the results from the other specifications may be driven by young researchers jumping on a bandwagon.

We find that varying the definition of novel inputs and expanding the set of novel concepts that we consider does not qualitatively alter the results we report in the main text. In columns 1 and 3-7 we see as before that authors in career year 1-10 are most likely to adopt newer ideas, followed by authors in career year 11-20, 21-30, and finally 31-40. In column 2, we see the mean age of the newest ideas in papers by authors in career age 1-10 are about four years newer than the newest ideas referenced by authors in career age 31-40; about three years newer than the newest ideas referenced by authors in career age 21-30; and 1.3 years newer than the newest ideas referenced by authors in career age 11-20. These results all confirm the robustness of the results we report in the main text.

In Table S5 we vary the time period and the types of articles included in the analysis. In all cases the comparison group is articles published in the same year by the same number of authors. The set of dummy variables employed correspond to the comparison groups. In all cases only first author-article pairs are considered.

In columns 1-3 we vary the time period. In column 1 only articles published in 1980-1989 are considered. In column 2 only articles published in 1990-1999 are considered. In column 3 only articles published in 2000-2008 are considered.

In columns 4-6 we vary the set of articles included in the analysis. The time period is again 1980-2008. In column 4 all regular research articles are considered. In column 5 all articles are considered. In column 6 only regular research articles published by authors located in the US are considered; the time period for this analysis is 1988-2008 as location information is mainly only available for articles published since 1988.

This table shows that varying the time periods that we consider does not lead to qualitatively different conclusions to the ones we report in the main text. As before, authors in career year 1-10 are most likely to adopt newer ideas, followed by authors in career age 11-20, 21-30, and 31-40.

In Table S6 we employ research area or journal specific comparison groups. In all cases the set of dummy variables correspond to the comparison groups. Only first author-article pairs are considered.

In column 1 the comparison group is articles that are published in the same year and are indexed with the same MESH "Diseases" terms (the C terms in MESH, only "major topic" terms are considered). This corresponds to applied research.

In column 2 the comparison group is articles that are published in the same year and are indexed with the same MESH "Anatomy" terms (the A terms in MESH, only "major topic" terms are considered). This too corresponds to applied research.

In column 3 the comparison group is articles that are published in the same year and are indexed with the same MESH "Organisms" terms (the B terms in MESH, only "major topic" terms are considered). So that this analysis is representative of basic research, we exclude any articles that are indexed with a MESH disease term (the C terms in MESH, both "major topic" and "minor topic" terms are considered).

In column 4 the comparison group is articles that are published in the same year and are indexed with the same MESH "Chemicals and Drugs" terms (the D terms in MESH, only "major topic" terms are considered). So that this analysis is representative of basic research, we exclude any articles that are indexed with a MESH disease term (the C terms in MESH, both "major topic" and "minor topic" terms are considered).

In column 5 the comparison group is articles that are published in the same year and are indexed with the same MESH "Phenomena and Processes" terms (the G terms in MESH, only "major topic" terms are considered). So that this analysis is representative of basic research, we exclude any articles that are indexed with a MESH disease term (the C terms in MESH, both "major topic" and "minor topic" terms are considered).

In constructing the comparison groups used in the analyses of columns 1-5, we first truncate all MESH codes to 7 characters (i.e. C11.294.177 becomes C11.294 and then require that all such 7 character codes are the same in two papers for them to be in the same comparison group. Also 3 character MESH codes are considered (i.e. C11) but all articles in a comparison group are excluded from the analysis when the comparison group consists of the identifier for the comparison group consists of a lone 3 character MESH code.

In column 6 the comparison group is articles that are published in the same journal in the same year and have the same number of authors.

As was the case with the previous tables, these results confirm the results in our main text. Thus, varying the set of papers we include in the analysis based on the MESH field does not change the relative probabilities of authors of different career stages trying out new ideas. Similarly, focusing our attention on within-journal variation produces the same conclusion; that is, even within a fixed journal, on average authors in career stage 1-10 are the most likely to try out newer ideas.

In the second parametric specification, we test the robustness of Figure 3 from the main paper. To do this, we regress the outcome variable (whether a paper is a top 20% paper based on the novelty of its idea inputs) on the following 9 indicator variables:

- **(Young, Young)**, which is 1 if both authors have career age 0-10 (and is 0 otherwise, obviously).
- **(Young, Middle)**, which is 1 if first author's career age is 0-10, last author's career age is 11-25.
- **(Young, Old)**, which is 1 if first author's career age is 0-10, last author's career age is 26-40.
- **(Middle, Young)**, which is 1 if first author's career age is 11-25, last author's career age is 0-10.
- **(Middle, Middle)**, which is 1 if first author's career age is 11-25, last author's career age is 11-25.
- **(Middle, Old)**, which is 1 if first author's career age is 11-25, last author's career age is 26-40.

- **(Old, Young)**, which is 1 if first author's career age is 26-40, last author's career age is 0-10.
- **(Old, Middle)**, which is 1 if first author's career age is 26-40, last author's career age is 11-25.
- **(Old, Old)**, which is 1 if first author's career age is 26-40, last author's career age is 26-40.

In reporting the results, we designate the last group **(Old, Old)** as the omitted group. First and foremost, results from this second specification reveal to which extent our finding in the main text, that teams with a young first author and a more seasoned last author have a higher propensity to try out new ideas than other team configurations, holds across the different sensitivity analyses. To the extent that the finding holds, we would expect that:

1. The coefficient on the dummy variables **(Young, Middle)** and **(Young, Old)** are positive, indicating that the propensity to try out new ideas is higher for teams with an early career first author and a mid- or a late-career last author than researchers in the omitted group (teams with late-career first and last authors).
2. The coefficient on the dummy variable **(Young, Middle)** is higher than any estimated coefficient.
3. The coefficient on the dummy variable **(Young, Old)** is the second-highest of the estimated coefficients.

In reading the regression tables reported below, the reader should thus examine whether estimates of the coefficient on the dummy variable **(Young, Middle)** is positive and the highest among the estimated coefficients and that the coefficient on the dummy variable **(Young, Old)** too is positive and the second-highest among the estimated coefficients. **The expected pattern indeed emerges across all specifications.**

Unless otherwise noted, the outcome variable is the indicator variable that captures whether a paper is among the top 20% based on how recent is the newest idea input, with idea inputs represented by the top 100 concepts in each cohort. In all cases the dummy variables correspond to the comparison groups based on which the outcome variable is constructed.

As in the non-parametric analyses and the above parametric analyses, we weight observations so that the total weight of observations from any given year is the same as the total weight of observations from any other year.

In Table S7 we report estimates from this second regression strategy.

In columns 1-2 we vary the set of articles considered. In column 1 all regular research articles are considered. In column 2 only regular articles by authors located in the US are considered. In both cases the comparison group is articles published in the same year by the same number of authors.

In columns 3-4 we employ research area specific comparison groups. In column 3 the comparison group is constructed based on MESH "Disease" terms (similar to column 1 of Table S6, see above). In column 4 the comparison group is constructed based on MESH "Phenomena and Processes" terms (similar to column 5 in Table S6, see above).

In column 5 the comparison group is articles published in the same year in the same journal.

In column 6 we vary the outcome variable. The outcome variable is the indicator variable that captures whether the paper is among the top 5% newest based on the age of the newest idea input. The comparison group is articles published in the same year by the same number of authors.

In column 7 we vary also the set of concepts considered in constructing the outcome variable. In this column, the set of concepts considered in the analysis is the top 10,000 concepts in each cohort. As in column 6, the outcome variable is the indicator variable that captures whether the paper is among the top 5% newest based on the age of the newest idea input.

Finally, in column 8 we employ the alternative disambiguation (see Section A.4).

Since the top three sets of rows in every column are larger than the coefficients in the rows below, we conclude that young first authors are the most likely to try out new ideas, regardless of the career stage of the last author. Furthermore, a young first author paired with a mid-career last author is the team configuration that is most likely to try out new ideas. This is exactly the pattern we report in our non-parametric analysis in the main text of the paper.

In Table S8 we further extend the analysis to study whether the above results are robust to considering also the career age of the second author. We only consider papers with three or more authors, and now regress the outcome variable (whether a paper is a top 20% paper based on the novelty of its idea inputs) on 27 indicator variables which capture the career stage of the first, second and last author. For example, the variable **(Young, Young, Young)** is 1 if the first author, the second author, and also the last author have career age 0-10 (and is 0 otherwise), and the variable **(Middle, Young, Old)** is 1 if the first author's career age is 11-25, the second author's career age is 0-10, and the last author's career age is 26-40 (and is 0 otherwise). In reporting the results, we designate the group **(Old, Old, Old)** as the omitted group.

The outcome variable is again the indicator variable that captures whether a paper is among the top 20% based on how recent is the newest idea input, with idea inputs represented by the top 100 concepts in each cohort. In all cases the "fixed effects" dummy variables correspond to the comparison groups based on which the outcome variable is constructed. We again weight observations so that the total weight of observations from any given year is the same as the total weight of observations from any other year.

In column (1) the comparison group is all articles published in the same year by the same number of authors. In column (2) group is all articles published in the same year. In column (3) the comparison group is all articles indexed with the same disease MESH terms and published in the same year. In column (4) articles linked to a disese are excluded and the comparison group is all articles indexed with the same phenomena and processes MESH terms and published in the same year.

Across the specifications, the results indicate that our main finding from the above analysis is robust: teams that have the highest propensity to try out new ideas have an experienced last author and a young first author. The estimate of the coefficient on the variable **(Young, Young, Middle)** is always highest (row 2), and the next two highest estimates are always the estimates of the coefficients on the variables **Young, Young, Old)** and **(Young, Middle, Middle)** (rows 3 and 5).

Because the estimates vary by the age of the second author, the results also show that the career stage of the second author does matter. That said, the results indicate that the first and last authors play the two key roles in terms of the propensity to try out new ideas: it is more important to have youth in the first author position than in the second author position and it is more important to have experience in the last author position than in the second author position. This is indicated by pairwise comparisons of estimates of the coefficients on the variables that are indicated with the same color (for those who cannot distinguish between all colors we have indicated these pairs also with characters " ❏ ", " ❍ ", " ❚ ", " ● ", " ◆ " and " ■ ') . Reversing the positions of a middle-career last author and a young second author markedly decreases the propensity to try out new ideas (as revealed by a comparison of estimates on lines colored in red and marked with character " ❍ "), as does reversing the positions of a young second author and a late-career last author (as revealed by a comparison of estimates on lines colored in orange and marked with character " ❏ "). Reversing the positions of a young first author and a mid-career second author also decreases the propensity to try out new ideas (as revealed by a comparison of estimates on lines colored in blue and marked with character " ❚ " as well as by a comparison estimates on lines colored in green and indicated with character " ● "). Finally, reversing the positions of a young first author and a late-career second author too decreases the propensity to try out new ideas (as revealed by a comparison of estimates on lines colored in brown and marked with character " ◆ " as well as by a comparison of estimates on lines colored in purple and marked with character " ■ ").

Table S2: Relationship between author career age and the trying out of new ideas: results for different author definitions (first authors; first and last authors; all authors), different comparison groups (articles published in the same year; articles published in the same year by the same number of authors); and different samples (papers which authors are listed in alphabetic order; papers which authors are listed in non-alphabetic order.)

In all columns, the dependent variable is top 20% status by the age of the newest idea input.

Explanations for the columns (which vary authorships considered and comparison group):

(1) First author-article pairs only, comparison group is all papers published in the same year by the same number of authors.
(2) First author-article pairs only, comparison group is all papers published in the same year.
(3) First and last author-article pairs only, comparison group is the same as in (1).
(4) All author article pairs, comparison group is the same as in (1).
(5) First author-article pairs for articles for which first and last author are listed in non-alphabetical order, comparison group is the same as in (1).
(6) First author-article pairs for articles for which all authors are listed in alphabetical order, comparison group is the same as in (1).

	(1)	(2)	(3)	(4)	(5)	(6)
Career Year 0	.027***	.022***	-.029***	-.014***	.024***	-.006
	(.002)	(.003)	(.002)	(.001)	(.003)	(.005)
Career Year 1-10	.070***	.078***	.027***	.025***	.067***	.055***
	(.002)	(.002)	(.001)	(.001)	(.002)	(.004)
Career Year 11-20	.036***	.042***	.026***	.019***	.037***	.042***
	(.001)	(.001)	(.001)	(.001)	(.002)	(.003)
Career Year 21-30	.010***	.013***	.013***	.009***	.013***	.019***
	(.001)	(.002)	(.001)	(.001)	(.002)	(.003)
Observations	6,421,201	6,422,775	12,206,501	28,811,988	3,410,385	1,252,961
Fixed Effects	706	29	788	1,776	587	305
Mean for **Career Year 31-40**	.011***	.014***	.013***	.009***	.013***	.019***
	(.001)	(.002)	(.001)	(.001)	(.002)	(.003)

"Fixed Effects" reports the number of additional dummy variables included in the analysis;
these fixed effects correspond to the comparison groups.
"Mean for **Career Year 31-40**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S3: Relationship between author career age and the trying out of new ideas: results for different author disambiguation approaches (existing 'Author-ity' disambiguation; our own alternative disambiguation), and for within-career comparisons.

In all columns, the dependent variable is top 20% status by the age of the newest idea input.

Explanations for the columns (which vary authorships considered and comparison groups):

In columns (1)-(2) the comparison group is all papers published in the same year by the same number of authors.
(1) First author-article pairs only, 'Author-ity' author name disambiguation (the same analysis analysis as in column 1 of Table S2).
(2) First author-article pairs only, our own alternative author name disambiguation
In columns (3)-(5) the comparison group is all articles published by the same author.
(3) First author-article pairs only. Comparison group is all papers published in the same year.
(4) First author-article pairs only. Comparison group is all papers published in the same year.
(5) First and last author-article pairs only. Comparison group is the same as in column (3).
(6) All author-article pairs. Comparison group is the same as in column (3).

	(1)	(2)	(3)	(4)	(5)	(6)
Career Year 0	.026***	.007***	.008***	.021***	.019***	.010***
	(.002)	(.002)	(.002)	(.002)	(.001)	(.001)
Career Year 1-10	.069***	.057***	.011***	.026***	.013***	.013***
	(.002)	(.002)	(.002)	(.002)	(.001)	(.001)
Career Year 11-20	.036***	.028***	.001	.015***	.004***	.004***
	(.001)	(.001)	(.002)	(.002)	(.001)	(.001)
Career Year 21-30	.010***	.004**	-.002	.006***	.001*	.000
	(.001)	(.001)	(.002)	(.002)	(.001)	(.001)
Observations	6,421,201	3,191,593	5,396,076	5,397,495	26,493,346	10,789,179
Fixed Effects	706	621	1,085,278	1,085,362	2,723,817	1,421,129
Mean for **Career Year 31-40**	.151	.165	.189	.176	.162	.170
	(.001)	(.001)	(.002)	(.002)	(.001)	(.001)

"Fixed Effects" reports the number of additional dummy variables included in the analysis;
these fixed effects correspond to the comparison groups (columns 1-2) and authors (columns 3-5).
"Mean for **Career Year 31-40**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S4: Relationship between author career age and the trying out of new ideas: results for different sets of idea inputs (top 100 with and without sensitivity exclusions; top 1,000; top 10,000 in each cohort) and for different ways of calculating novelty of idea inputs (top 20% status in terms of age of idea inputs; top 5% status in terms of age of idea inputs; raw age of newest idea input; whether mentions of a novel idea that has been mentioned in no more than 50 prior papers).

In all columns, the comparison group is articles with the same number of authors and published in the same year.

Explanations for the columns (which vary the way the dependent variable is calculated):

In columns (1)-(2) dependent variable calculated based on mentions of top 100 new ideas in each cohort.
(1) Dependent variable measures top 5% status by age of newest idea input.
(2) Dependent variable measures raw age of newest idea input.
In columns (3-4) dependent variable measures top 20% status by age of newest idea input.
(3) Dependent variable calculated based on mentions of top 1,000 concepts in each cohort.
(4) Dependent variable calculated based on mentions of top 10,000 concepts in each cohort.
In columns (5-6) dependent variable measures top 20% status by age of newest idea input and is calculated based on mentions of top 100 concepts in each cohort.
(5) Dependent variable is calculated after excluding mentions of concepts marked with "exclude for sensitivity analysis" in the embedded list see Section A.2 above) are excluded.
(6) Dependent variable is calculated after excluding mentions of concepts in the year in which they were first mentioned in the data (cohort year).
(7) Dependent is a dummy variable that captures whether the paper mentions a top 100 concept from some cohort before the year in which the concept is mentioned for the 50th time in the MEDLINE data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Career Year 0	.008***	-.611***	.037***	.057***	.023***	.026***	.0018***
	(.001)	(.069)	(.002)	(.002)	(.002)	(.002)	(.0002)
Career Year 1-10	.020***	-2.291***	.073***	.071***	.069***	.070***	.0022***
	(.001)	(.057)	(.001)	(.001)	(.002)	(.002)	(.0002)
Career Year 11-20	.009***	-1.429***	.036***	.033***	.036***	.036***	.0004**
	(.001)	(.037)	(.001)	(.001)	(.001)	(.001)	(.0002)
Career Year 21-30	.002***	-.538***	.012***	.012***	.010***	.011***	.0000
	(.001)	(.032)	(.001)	(.001)	(.001)	(.001)	(.0002)
Observations	6,421,201	6,421,201	6,421,201	6,421,201	6,421,201	6,421,201	6,421,201
Fixed Effects	706	706	706	706	706	706	706
Mean for **Career Year 31-40**	.036	23.832	.147	.145	.152	.151	.0040
	(.001)	(.045)	(.001)	(.001)	(.001)	(.001)	(.0002)

"Fixed Effects" reports the number of additional dummy variables included in the analysis;
these fixed effects correspond to the comparison groups.
"Mean for **Career Year 31-40**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S5: Relationship between author career age and the trying out of new ideas: results for different time periods (1980s; 1990s; 2000s) and for selections of articles (only regular research articles; all articles; only regular research articles published by authors located in the US)

In all columns, the dependent variable is top 20% status by the age of the newest idea input and comparison group is articles published in the same year by the same number of authors.

Explanations for the columns (which vary the time period and the types of research articles included in the sample):

(1) Sample period is 1980-1989.
(2) Sample period is 1990-1999.
(3) Sample period is 2000-2008
In columns (4-5) the sample period is 1980-2008.
(4) Only regular research articles are included in the sample (the same analysis analysis as in column 1 of Table S2).
(5) All journal articles are included in the sample.
In column (6) the sample period is 1988-2008.
(6) Only regular research articles published by authors located in the US are included in the sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Career Year 0	.032***	.038***	.008**	.027***	.019***	.029***
	(.003)	(.003)	(.003)	(.002)	(.003)	(.005)
Career Year 1-10	.075***	.077***	.057***	.070***	.067***	.080***
	(.003)	(.002)	(.002)	(.002)	(.002)	(.006)
Career Year 11-20	.041***	.038***	.029***	.036***	.039***	.039***
	(.003)	(.002)	(.002)	(.001)	(.001)	(.005)
Career Year 21-30	.015***	.007***	.012***	.011***	.014***	.015*
	(.003)	(.002)	(.002)	(.001)	(.001)	(.006)
Observations	1,306,028	2,106,144	3,009,029	6,421,201	8,577,485	1,757,270
Fixed Effects	133	182	391	706	725	550
Mean for **Career Year 31-40**	.146	.146	.162	.151	.154	.144
	(.003)	(.002)	(.002)	(.001)	(.002)	(.005)

"Fixed Effects" reports the number of additional dummy variables included in the analysis;
these fixed effects correspond to the comparison groups.
"Mean for **Career Year 31-40**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S6: Relationship between author career age and the trying out of new ideas: results for research area or journal specific comparisons.

In all columns, the dependent variable is top 20% status by the age of the newest idea input.

Explanations for the columns (which vary the comparison group):

(1) Comparison group is articles indexed with the same disease terms in the same year.
(2) Comparison group is articles indexed with the same anatomy terms in the same year.
(3) Comparison group is articles indexed with the same organism terms in the same year; articles indexed to a disease term are excluded.
(4) Comparison group is articles indexed with the same chemicals and drugs terms in the same year; articles indexed to a disease term are excluded.
(5) Comparison group is articles indexed with the same phenomena and processes terms in the same year; articles indexed to a disease term are excluded.
(6) Comparison group is articles published in the same journal in the same year with the same number of authors.

	(1)	(2)	(3)	(4)	(5)	(6)
Career Year 0	.026***	.041***	.052***	.035***	.028***	.030***
	(.002)	(.002)	(.003)	(.002)	(.003)	(.001)
Career Year 1-10	.051***	.063***	.082***	.054***	.056***	.045***
	(.002)	(.002)	(.003)	(.002)	(.003)	(.001)
Career Year 11-20	.025***	.035***	.047***	.031***	.033***	.027***
	(.002)	(.002)	(.003)	(.002)	(.003)	(.001)
Career Year 21-30	.006**	.013***	.015***	.011***	.011***	.011***
	(.002)	(.002)	(.004)	(.003)	(.003)	(.001)
Observations	1,714,208	1,805,828	725,282	1,390,933	985,553	5,763,277
Fixed Effects	70,343	47,241	9,189	52,518	29,596	297,101
Mean for **Career Year 31-40**	.150	.142	.131	.145	.146***	.147
	(.002)	(.002)	(.003)	(.002)	(.003)	(.001)

"Fixed Effects" reports the number of additional dummy variables included in the analysis;
these fixed effects correspond to the comparison groups.
"Mean for **Career Year 31-40**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S7: Relationship between team characteristics (career age of first and last author) and the trying out of new ideas.

Explanations for the columns (which vary the comparison group, disambiguation, sample, and the way the dependent variable is calculated).

In columns (1)-(5) and (8) the dependent variable is top 20% status by age of newest idea input.
(1) Comparison group is all articles published in the same year by the same number of authors.
(2) Comparison group is all articles published in the same year.
(3) Comparison group is all articles indexed with the same disease terms and published in the same year.
(4) Comparison group is all articles indexed with the same phenomena and processes terms and published in the same year; articles linked to a disease are excluded.
(5) Comparison group is all articles published in the same journal in the same year.
(6) Same analysis as in column (1) but dependent variable is top 5% status by age of newest idea input.
(7) Same analysis as in column (6) but now age of newest idea input is calculated based on mentions of top 10,000 concepts in each cohort (as opposed to the top 100 concepts in each cohort).
(8) Same analysis as in column (1) but career ages calculated based on our alternative author name disambiguation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Young, Young)	.023***	.033**	.026***	.035***	.039***	.011***	.026***	-.001
	(.003)	(.010)	(.003)	(.005)	(.002)	(.001)	(.001)	(.004)
(Young, Middle)	.075***	.085***	.053***	.061***	.044***	.024***	.023***	.071***
	(.002)	(.009)	(.003)	(.005)	(.002)	(.001)	(.001)	(.002)
(Young, Old)	.052***	.058***	.039***	.040***	.028***	.015***	.014***	.040***
	(.002)	(.009)	(.003)	(.005)	(.002)	(.001)	(.001)	(.002)
(Middle, Young)	-.001	-.002	.006	.014**	.021***	.002	.012***	-.008*
	(.002)	(.011)	(.003)	(.005)	(.002)	(.001)	(.001)	(.003)
(Middle, Middle)	.035***	.040***	.023***	.037***	.026***	.011***	.012***	.039***
	(.002)	(.009)	(.003)	(.005)	(.002)	(.001)	(.001)	(.003)
(Middle, Old)	.018***	.037***	.009**	.022***	.011***	.004***	.003***	.017***
	(.002)	(.010)	(.003)	(.005)	(.002)	(.001)	(.001)	(.003)
(Old, Young)	-.028***	-.001	-.017***	-.014*	-.000	-.005***	.005***	-.031***
	(.002)	(.016)	(.004)	(.006)	(.002)	(.001)	(.001)	(.003)
(Old, Middle)	.007**	.033*	.002	.013*	.008**	.003**	.005***	.018***
	(.002)	(.017)	(.004)	(.006)	(.002)	(.001)	(.001)	(.003)
Observations	4,668,963	1,270,596	1,351,294	694,928	4,163,506	4,668,963	4,668,963	1,505,399
Fixed Effects	651	493	55,852	21,378	215,746	651	651	506
Mean for **(Old, Old)**	.158	.148	.155	.147	.149	.036	.032	.168
	(.002)	(.008)	(.003)	(.005)	(.002)	(.001)	(.001)	(.002)

"Fixed Effects" reports the number of additional dummy variables included in the analysis; these fixed effects correspond to the comparison groups.
"Mean for **(Old, Old)**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table S8: Relationship between team characteristics (career age of first, second and last author) and the trying out of new ideas.

In all columns, the dependent variable is top 20% status by the age of the newest idea input.

Explanations for the columns (which vary the comparison group):

(1) Comparison group is all articles published in the same year by the same number of authors.
(2) Comparison group is all articles published in the same year.
(3) Comparison group is all articles indexed with the same disease terms and published in the same year.
(4) Comparison group is all articles indexed with the same phenomena and processes terms and published in the same year; articles linked to a disease are excluded.

	(1)		(2)		(3)		(4)	
(1) **(Young, Young, Young)**	.052***	(.005)	.041***	(.006)	.060***	(.008)	.084***	(.012)
(2) **(Young, Young, Middle)** ❍	.109***	(.005)	.102***	(.005)	.089***	(.008)	.111***	(.012)
(3) **(Young, Young, Old)** ❏	.085***	(.005)	.079***	(.005)	.076***	(.008)	.089***	(.012)
(4) **(Young, Middle, Young)** ❍	.039***	(.005)	.027***	(.005)	.050***	(.008)	.080***	(.012)
(5) **(Young, Middle, Middle)** ▮	.083***	(.005)	.072***	(.005)	.072***	(.008)	.097***	(.012)
(6) **(Young, Middle, Old)** ●	.066***	(.005)	.059***	(.004)	.061***	(.008)	.081***	(.012)
(7) **(Young, Old, Young)** ❏	.025***	(.005)	.010	(.006)	.039***	(.008)	.062***	(.013)
(8) **(Young, Old, Middle)** ◆	.070***	(.005)	.052***	(.005)	.065***	(.008)	.085***	(.013)
(9) **(Young, Old, Old)** ■	.051***	(.005)	.038***	(.004)	.051***	(.008)	.062***	(.013)
(10) **(Middle, Young, Young)**	.032***	(.005)	.021***	(.005)	.043***	(.008)	.066***	(.012)
(11) **(Middle, Young, Middle)** ▮	.070***	(.005)	.069***	(.005)	.063***	(.008)	.088***	(.012)
(12) **(Middle, Young, Old)** ●	.051***	(.005)	.052***	(.004)	.048***	(.008)	.067***	(.013)
(13) **(Middle, Middle, Young)**	.011*	(.005)	.005	(.005)	.029***	(.008)	.047***	(.013)
(14) **(Middle, Middle, Middle)**	.043***	(.005)	.044***	(.004)	.039***	(.008)	.072***	(.013)
(15) **(Middle, Middle, Old)**	.033***	(.005)	.036***	(.004)	.029***	(.008)	.066***	(.013)
(16) **(Middle, Old, Young)**	-.008	(.006)	-.014**	(.005)	.006	(.009)	.037*	(.015)
(17) **(Middle, Old, Middle)**	.026***	(.005)	.022***	(.005)	.028**	(.009)	.050***	(.014)
(18) **(Middle, Old, Old)**	.020***	(.005)	.020***	(.004)	.016	(.009)	.051***	(.014)
(19) **(Old, Young, Young)**	.004	(.005)	-.006	(.005)	.021*	(.008)	.039**	(.013)
(20) **(Old, Young, Middle)** ◆	.043***	(.005)	.042***	(.005)	.045***	(.008)	.064***	(.013)
(21) **(Old, Young, Old)** ■	.033***	(.005)	.033***	(.004)	.036***	(.009)	.047***	(.014)
(22) **(Old, Middle, Young)**	-.012*	(.005)	-.019***	(.004)	.004	(.009)	.014	(.014)
(23) **(Old, Middle, Middle)**	.017***	(.005)	.010	(.011)	.022*	(.009)	.037**	(.013)
(24) **(Old, Middle, Old)**	.019***	(.005)	.022***	(.004)	.030**	(.009)	.043**	(.015)
(25) **(Old, Old, Young)**	-.022***	(.006)	-.029***	(.006)	-.006	(.010)	.003	(.017)
(26) **(Old, Old, Middle)**	.001	(.006)	-.003	(.006)	.003	(.010)	.049**	(.018)
Observations	4,628,517		4,630,084		1,335,724		689,142	
Fixed Effects	649		29		55,397		21,267	
Mean for **(Old, Old, Old)**	.134	(.005)	.142	(.005)	.125	(.008)	.101	(.012)

"Fixed Effects" reports the number of additional dummy variables included in the analysis;
these fixed effects correspond to the comparison groups.
"Mean for **(Old, Old, Old)**" reports the mean of the dependent variable for the omitted group.
Standard errors in parentheses; robust to correlation within groups corresponding to fixed effects.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Web Appendix References

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