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Breakthrough Recognition: Bias Against Novelty and Competition for Attention

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Abstract

Adding to the literature on the recognition and spread of ideas, and alongside the bias against novelty view documented in prior research, we introduce the perspective that articles compete for the attention of researchers who might build upon them. We investigate this effect by analyzing more than 5.3 million research publications from 1970 to 1999 in the life sciences. In support of our competition for attention perspective, we show that articles covering rarely addressed topics tend to receive more citations and have a higher chance of being breakthrough papers as compared to articles on more popular topics. We also explore conditions under which these effects might vary by using decade subsamples, home- versus foreign-field forward citations, as well as short-, medium- and long-term time windows. Finally, we also find evidence consistent with the previously documented bias against novelty and show that both mechanisms can work simultaneously.

Introduction

Due to its cumulative nature, the advancement of knowledge depends not only on creativity and the quality of an idea itself, but also on whether the scientific community in which the idea emerges recognizes and builds upon it (Furman and Stern 2011; Newton 1676). Hence, the idea at the core of a successful scientific breakthrough that lays the foundations for further advancements must not only be significantly novel but must also be recognized by others (Simonton 1999). Even if a creative idea is of high quality, its recognition is key but difficult as there can be significant delays and no guarantee that the idea will be recognized at all. For instance, Barbara McClintock's discovery of mobile genetic elements in maize in the 1940s (McClintock 1941, 1950), which was crucial to further understanding of genetics and genetic control, was not recognized until the 1960s and only awarded a Nobel Prize in 1983 (Nobelprize.org).

The consumption and recognition of knowledge is usually facilitated when ideas fit within the confines of an accepted paradigm (Berson 1992; Kuhn 1962; Margolis 1993). But given that path-breaking advances usually have to break away from prevailing theories and paradigms (Kuhn 1962; Simonton 1999) and tend to make novel recombination of ideas from distant and diverse sources (Fleming 2001; Hargadon and Sutton 1997), their acceptance and recognition may be difficult and not immediate (Garfield 1980; Van Raan 2004). In fact, there is a bias against idea novelty, as idea recognition is usually facilitated when similar or closer ideas are recombined (Fleming et al. 2007; Mueller et al. 2012; Rietzschel et al. 2010; Wang et al. 2017). Taken together, it has been argued that while novel atypical combinations are key to the *creation* of breakthrough ideas, they should also encompass many conventional combinations to facilitate *recognition* (Uzzi et al. 2013).

Aside from the bias against novelty, another mechanism that may influence the

recognition of ideas is attention. Given the overabundance of information that audiences face, information overload is common, and attention is increasingly becoming a scarce resource (Bordalo et al. 2016; Hansen and Haas 2001; Iyer and Katona 2016; Shen et al. 2015; Van Knippenberg et al. 2015). Researchers, like everyone else, have limited time, attention, and cognitive resources to expend when searching publications for new scientific knowledge. Hence, ideas that emerge in crowded topical areas will have to compete harder for the attention of the scientific community, thereby lowering their chances of being recognized; while those that emerge in relatively lonely topical areas will not face such stiff competition for attention. For example, the trigger mechanism to RNA interference of gene silencing was discovered in the same year by two separate groups, one in plant research using potatoes (Waterhouse et al. 1998) and one in animal research using *c.elegans* worms as the model organism (Fire et al. 1998). Plant researchers had been working on understanding the phenomenon since the early 1990s; by contrast, it was a relatively unpopulated area for animal researchers. Not surprisingly, then, the paper using potatoes got lost in the crowd, while the one using *c.elegans* worms caught on.

The two mechanisms of breakthrough recognition – bias against novelty and competition for attention – are analogous to the ecological perspective of density dependence (Hannan and Carroll 1992). In population ecology, the density dependence argument explores the interplay between competition and legitimacy at the organizational level. When a new domain emerges, organizations operating in it are less known and have limited legitimacy. Similarly, when breakthrough ideas emerge, there is stronger bias against their novelty due to their lack of familiarity and legitimacy in the scientific community. This novelty usually stems from the recombination of more distant and diverse sources (Fleming 2001; Hargadon and Sutton 1997). Hence, an article that includes familiar recombinations is more likely to be noticed and accepted since its ideas already fit within the confines of established theory (Kuhn 1962; Margolis 1993).

However, at the same time, because the domain is new, it tends to be less crowded, and there is less competition between organizations. Similarly, in the idea space, if the domain in which the breakthrough idea emerged is not yet crowded, there is limited competition for attention. Thus, an article addressing a certain domain is more likely to be picked up when there are fewer other articles addressing that domain at that point in time and consequently less competition. Because of these tensions, we also explore implications of the interplay between the two mechanisms.

To the best of our knowledge, the innovation literature on breakthrough recognition has extensively addressed the mechanism of bias against novelty (Fleming et al. 2007; Kuhn 1962; Margolis 1993; Mueller et al. 2012; Rietzschel et al. 2010; Wang et al. 2017), while the competition for attention view – the notion that ideas are competing for researchers’ attention – has been underexplored. We contribute to the literature on breakthrough recognition and investigate our hypothesis by analyzing more than 5.3 million research publications spanning three decades (1970 to 1999) in the life sciences from the Web of Science and MedLine (Torvik and Smalheiser 2009). In keeping with the competition for attention view, our data indicate that papers covering topics frequently covered by other papers published in the same year tend to receive far fewer citations than papers covering much less frequently addressed topics. They also have a much lower chance of being in the top 1% of forward citations for papers published in that field and year. In other words, papers that address rarely covered topics have a much higher chance of being recognized and built upon by the scientific community. Furthermore, our analysis explored conditions that moderate the effect of the mechanism of competition for attention using decade subsamples, home versus foreign field forward citations, as well as short-, mid-, and long-term time windows to run additional analyses on top of the main effects. Our data also corroborate the previous findings on the bias against novelty and support of a simultaneous

process where both mechanisms could be thought of as operating in tandem, as predicted by the density dependence theory.

From a policy and managerial standpoint, our findings provide a new dimension for decision makers who are looking to optimize public and private investment in science and technology in search of the next breakthrough idea.

Recognition of Breakthrough Ideas

Since Schumpeter's notion of creative destruction (1942), scientific and technological breakthroughs have held a central and recurrent prominence in the innovation literatures (Azoulay et al. 2010; Burt 2004; Girotra et al. 2010; Jones 2009; Kuhn 1962; Simonton 1989; Simonton 1999; Singh and Fleming 2010; Wuchty et al. 2007). The topic remains extremely important, as breakthroughs have the potential to disrupt extant industries and regions, while also providing impetus for new industries, economies, and society as a whole (Rosenberg 1974). For breakthroughs to occur, they depend not only on the quality of the idea itself, but also on whether they are recognized and built upon by the community (Simonton 1999). Both components – generation and recognition – are crucial for such breakthroughs, as one cannot simply assume that the more groundbreaking an idea is, the more impact it will have, and/or the more likely it is to be recognized and built upon by the scientific community.

Bias Against Novelty in the Recognition of Ideas

In fact, a main reason for the difficulty in recognizing breakthrough ideas is the bias against novelty, which directly stems from the recombinant process underlying the generation of novel, path-breaking ideas (Fleming 2001; Henderson and Clark 1990; Weitzman 1998). The creative search process in breakthrough discovery is enhanced with the combination of diverse knowledge stemming from different individuals (Singh and Fleming 2010; Wuchty et al. 2007),

different experiences (Arts and Fleming 2018; McEvily and Zaheer 1999), or different network positions (Burt 2004). This notion of combinatorial novelty is prevalent in the innovation literature and has been directly employed and studied in settings pertaining to both scientific and technological innovation using peer-reviewed publications (Azoulay et al. 2012; Boudreau et al. 2016; Uzzi et al. 2013) and patents (Fleming 2001; Verhoeven et al. 2016).

This aforementioned diversity is key to avoiding myopia and breaking away from prevailing theories and assumptions on the path to creating breakthrough advances (Chai 2017; Hargadon and Sutton 1997; Kuhn 1962; Lifshitz-Assaf 2017; Simonton 1999). Although the recombination of more distant ideas may increase the likelihood of producing path-breaking novelty, these ideas still need to be recognized to be considered breakthroughs. In fact, the literature has often documented that the consumption and recognition of knowledge is usually facilitated when similar or closer ideas are recombined (Fleming et al. 2007; Wang et al. 2017), as they are more likely to fit within the confines of the accepted paradigm (Kuhn 1962; Margolis 1993). When new breakthrough ideas emerge, existing paradigmatic forces may lead to resistance of the new competing paradigms. The old paradigm is incommensurable with the new one, and proponents of each will have difficulty engaging in meaningful conversations concerning the conflicting schools of thought (Kuhn 1962). It is precisely because of these more distant and less familiar recombinations that recognition of these groundbreaking novelties may be delayed (Garfield 1980; Van Raan 2004) or hindered (Fleming et al. 2007; Wang et al. 2017). Hence, there is a bias against novelty in the recognition of breakthrough ideas.

This aversion to newness can stem from a lack of legitimacy (Hannan and Carroll 1992). Like entrepreneurial firms, new ideas face a liability of newness (Stinchcombe 1965). New ideas lack a proven track record and a positive image or reputation (Aldrich and Kim 2007). They are challenged by their untested nature (Nerkar and Shane 2007; Zahra and Nielsen 2002).

People may also have a cognitive reluctance to accepting novelty. Novelty and creativity are often associated with the aversive state of uncertainty (Mueller et al. 2012). Hence, although individuals openly assert that creativity is the fundamental driving force for scientific and technology advancement (Hennessey and Amabile 2010), they still tend to routinely reject creative ideas and instead select more feasible and desirable ideas at the cost of originality (Rietzschel et al. 2010). This tension has also been documented in the context of cognitive distance between alliance partners and their subsequent innovation performance. Novelty increases, but the consumption or absorption of this novelty decreases with cognitive distance (Nooteboom et al. 2007).

Uzzi et al. (2013) offer a partial resolution of this tension by proposing that novel atypical combinations within an article are key to the creation of breakthrough ideas, although breakthrough papers also tend to include many conventional combinations, thus straddling the two effects. Also speaking to this essential tension between productive tradition and risky innovation, Foster et al. (2015) find that for prize winners in biomedicine and chemistry, occasional gambles for extraordinary impact account for the observed levels of risky breakthrough innovation across a researcher's portfolio of publications.

Competition for Attention in the Recognition of Ideas

While the bias against novelty/creativity view has been very insightful, we propose that there is more than one mechanism driving the acceptance and recognition of groundbreaking ideas. Aside from the liability of newness that calls into question an idea's legitimacy, competition is another dimension that should be considered, as suggested by the density dependence argument in population ecology (Hannan and Carroll 1992). When a new domain emerges, organizations operating in it have limited legitimacy. At the same time, since the domain is emerging it is less crowded and less competition between organizations exists.

Translating this argument onto the idea space suggests a greater bias against novelty due to lack of legitimacy. However, since the domain is not yet crowded, there is also limited competition for attention.

Audiences' attention is at the core of what ideas compete for in the quest for further recognition and subsequent usage by the community. The focus on attention and attentional mechanisms has a long intellectual history. In their seminal work, Simon and Barnard (1947) argued that organizations could be thought of as structures that focus and channel the attention of their members. Several others have followed in this tradition (Cyert and March 1963; Daft and Weick 1984; March and Shapira 1987; March and Simon 1958) and explored how attention and its differential distribution in an organization can significantly affect organizational decision making. More recently, an attention-based view of the firm has been proposed (Ocasio 1997) that includes how rules and structures within an organization affect the distribution of the scarce resource of attention and decision making. Other work has noted how critical events can focus the attention of a community or field, and how that can affect institutional change (Hoffman and Ocasio 2001; Nigam and Ocasio 2010); and see (Ocasio 2011) for a review of the various traditions within organizational studies that have explored the importance of attention and attention allocation).

Attention also has a long tradition in cognitive psychology and, more recently, in neuroscience. The human attention system responds to stimuli entering our senses. When two or more visual stimuli are presented, they compete for processing resources (Bundesen 1990; Desimone and Duncan 1995; Pashler and Sutherland 1998). Mechanisms of selective attention (Driver 2001; Treisman 1969), which trace its roots back to William James (1890), support the selective processing of information relevant to our current goals and help individuals cope with and process complex environments. Hence, there are selective filters through which information

passes. In our context, the more crowded an area of study is, the more likely an article is to be filtered out without ever becoming a stimulus for attention (Broadbent 1958).

A recent stream of work in the organizational and marketing literatures has pointed out that people, products, and ideas have to compete for the attention of the audience they are trying to address (Hansen and Haas 2001; Iyer and Katona 2016; Ocasio 2011; Van Knippenberg et al. 2015). Given the information overload that customers face, decision makers, agents, and firms can develop strategic behaviors to compete to ensure that their products or ideas are attended to (Iyer and Katona 2016; Shen et al. 2015). Faced with market competition, firms have to strategically enhance certain product features to draw consumer attention (Bordalo et al. 2016). Recent digitization trends associated with the explosion of available electronic data has made attention a scarcer resource than information. Therefore, information senders have to compete for the attention of targeted receivers. When faced with an abundance of information, less offered information means more usage (Hansen and Haas 2001).

We borrow from these literatures and posit that a similar competition for attention mechanism is also at play in the domain of scientific publications. Ideas embedded in publications are constantly competing for the limited attention of other researchers in the scientific community. Papers that contain ideas that are commonly studied will compete for the attention of the community against all the other papers studying those ideas, while those papers that contain rarely studied ideas will not have to engage in such a tough fight for attention. Thus, we posit that ideas that are less commonly used by the broader scientific community will be more recognized as they don't need to compete as much for attention.

Along the same line of reasoning, the more topics a publication spans, the greater its odds are of being widely recognized. When a researcher explores and expands on existing knowledge, she usually searches using keywords. But given the researcher's limited attention, a paper

covering a broader set of topics has more keywords that researchers' can potentially search on. Hence, the paper is more likely to attract attention.

Competition for Attention and Bias Against Novelty

Having laid out the competition for attention mechanism, we now consider what one might expect in terms of observable patterns in idea recognition once both bias against novelty and competition for attention are taken into account simultaneously. The innovation literature is rather mute on the subject, given that one of the mechanisms, competition for attention, was borrowed from other literatures. However, as suggested by the density dependence theory (Hannan and Carroll 1992), there exists an interplay between competition and legitimacy. When a new domain emerges, organizations operating in it have limited legitimacy due to its newness. At the same time, new domains tend to be less crowded, and there is less competition between organizations as a result. Similarly, when a breakthrough idea emerges from combinational novelty, it has to overcome a liability of newness due to its lack of legitimacy. At the same time, if a breakthrough idea emerges in a less crowded domain, it faces less competition for the attention of audiences. Hence, we posit that the two processes act simultaneously on the recognition of breakthroughs.

Before we get to this interaction, we replicate the expected pattern from prior work that would result from the bias against novelty mechanism (Fleming et al. 2007; Mueller et al. 2012; Nooteboom et al. 2007; Wang et al. 2017), which is posited to affect the adoption of ideas by skewing recognition away from those that are highly novel, as captured by rare or distant combinations of topics.

For the joint action of both mechanisms, logically deducing from the arguments for each mechanism, one should expect that ideas with commonly covered topics will have to compete hard for attention (competition for attention), while common combinations of ideas will have an

easier time being adopted as the recombined idea has already gained traction and legitimacy (bias against novelty in reverse). Again, this is in line with the prediction of the density dependence argument (Hannan and Carroll (1992), presented earlier) from the organizational context translated to innovation and the spread of ideas.

Note that one of the channels concerns topics in a publication considered separately (how commonly studied they are), while the other concerns pairs or combinations of ideas (how common a given combination is). With this in mind, one should expect the greatest rate of adoption for ideas that cover topics less commonly addressed on their own, as they benefit from reduced competition for attention; but at the same time, these ideas are more commonly seen in combination, thus without being negatively biased by novelty. For example, continuing with the case of RNA interference, on top of writing in a less crowded space, the paper on *c.elegans* worms combined two keywords, *dsRNA* and *gene expression regulation*, that had been commonly combined in both the communities studying gene expression and interferon responses. The paper on potatoes, on the other hand, combined sense and antisense RNA with gene expression regulation, which was much less common. On the other hand, those ideas that cover topics that are commonly addressed by other publications (thus suffering from increased competition for attention), but are rarely paired/combined due to the novelty of the idea (thus also suffering from increased bias against novelty) will have the hardest time being adopted. A similar prediction should also be expected when using the span of topics in a publication as a measure of the competition for attention, as described earlier. Hence, publication recognition decreases when a publication covers fewer topics (thus attracting less attention) and when those topics are rarely studied together (thus also suffering from increased bias against novelty).

Data and Methods

We analyzed 5.3 million scientific publications in the life sciences published between 1970 and 1999. We focused on the life sciences to take advantage of the independent indexing of each publication using Medical Subject Heading (MeSH) keywords performed by indexers of the United States National Library of Medicine (NLM) at the National Institutes of Health. Since these controlled keywords are not assigned by the authors but by an independent indexer, they are believed to be a relatively objective classification scheme. It is therefore more difficult for authors to game the assignment of keywords by choosing those that are more or less popular at the time of publication or by introducing more or fewer keywords to manipulate the apparent breadth and depth of the article. Moreover, new MeSH keywords are only introduced into the lexicon once the phenomenon or concept has gained enough traction. For instance, the mechanism of RNA interference and its trigger¹ was discovered in 1998, but RNA interference only entered the MeSH lexicon in 2002. Therefore, although new MeSH keywords represent novel ideas or concepts, they are only added onto the MeSH lexicon after a new and steady stream of work has already been recognized. Hence, their frequency of use immediately after they are introduced is already high, and we do not run the risk of overestimating the novelty of subsequent papers assigned the new MeSH keywords.

We chose 1999 as the ending year of our sample to ensure that a total of 15 years had elapsed for every publication and that the collection of the longest specification of our dependent variables based on forward citations was accurate. Our data draws mainly from the disambiguated MedLine database² (Torvik and Smalheiser 2009), as it provides MeSH keywords and disambiguated author information. We supplemented this database using the Thomson

¹RNA interference is a breakthrough discovery in molecular biology that was awarded the 2006 Nobel Prize in Physiology or Medicine.

² MedLine is a database of references and abstracts on life sciences and biomedical topics maintained by the NLM.

Reuters Web of Science database by matching on the unique publication identification number (PMID) assigned on the MedLine database to obtain broad and narrow subfield classification for each article according to the subject area of the journal in which it was published. Our sample contains 178 unique narrow subfields and 16 broad subfields in the life sciences.

The main data is at the publication level. Table 1 shows the descriptive statistics, including the sample size, mean, standard deviation, and minimum and maximum of each variable used in our analyses. Table A1 in the Appendix shows the correlation matrix.

[Insert Table 1 about here]

Dependent variables

The consumption and recognition of scientific publications was proxied for by the widely-used measure of forward citations. We measured both the total number of citations that a paper garnered as well as whether or not the paper belonged to the top 1% of papers in terms of forward citations for all the papers published in that year and in that particular subfield.

Citations. We tabulated the number of forward citations that each publication garnered within 15 years, 10 years, and 3 years after its publication (*total cites 15yr, 10yr, and 3yr*). The three time windows were chosen to capture temporal patterns of forward citations, as prior research has shown that idea recognition is associated with a non-linear accumulation pattern.

Aside from the three time-window variants, we also separated citations into those from the same narrow subfield, i.e., home field citations and those from outside the narrow subfield, i.e., foreign field citations with 3-year, 10-year, and 15-year forward citations windows (*home cites 3yr, 10yr and 15yr*; and *foreign cites 3yr, 10yr, and 15yr*).

We also included the standard deviation of the number of forward citations in the 15-year window in order to plot dispersion graphs of the variable.

Top 1% of cites. To capture the right tail of the citation distribution—i.e., breakthrough papers—we use a binary variable indicating whether the number of total forward citations received by a publication is within the top 1% of the distribution of publications in terms of their total forward citations (with 3-year, 10-year, and 15-year time windows), clustered by year of publication and narrow subfield.

Independent variables

The competition for attention view was first proxied for by a measure of frequency using the number of times each MeSH keyword was assigned in the entire population of life sciences articles on an annual basis. In the three decades that our data covers, the number of distinct MeSHs per year ranged from 7,820 to 16,786. For each publication, the average frequency with which MeSHs of the focal publication were used to index other articles provides us an indication of how much attention the topics covered were receiving during the year it was published. As mentioned earlier, we also used the number of MeSH keywords assigned to each publication as another measure of competition for attention. Finally, to replicate the bias against novelty view, we also created a measure of combinatorial novelty.

Competition for Attention – average MeSH keyword frequency. For each MeSH keyword in the focal publication, we first tabulated the frequency with which it was used by all articles published in the same year (total count). Then, for each publication, we took the frequency of each of the MeSH keywords in that publication and calculated their average. The higher the average frequency, the more intense study the topics covered in the focal publication received from the scientific community. Since the average frequency values tend to be quite large, as shown in Table 1, the regressions were run with the normalized value of average frequency divided by 10,000.

Competition for Attention – number of MeSH keywords. We counted the number of MeSH keywords indexed for each focal publication. The higher the number of MeSH keywords used to index a publication, the more topics are covered in the focal publication, and the greater its odds are of being widely recognized

Combinatorial Novelty – average/median/maximum MeSH keyword dyad distance. For each dyadic combination of MeSH keywords in the focal publication, we first tabulated the frequency with which the same dyad appeared in all articles published in the same year (total count). The distance between each dyad is the reciprocal of the dyad frequency. Then, for each publication, we took the distance of each of the MeSH dyads in that publication and calculated their average. The higher this measure was, the more distant the ideas being recombined were, as less frequent MeSH co-occurrences indicate rarer recombination from farther idea spaces. We also calculated the median and the maximum dyad distance for each publication.

Control variables

Given prior research, we also included the following control variables:

Average cumulative publications. To address the possible but unlikely concern that highly skilled, more published authors would be more likely to work in low-frequency topics or tend to use more MeSH keywords, we also ran our analyses controlling for the average number of prior publications of the author team.³ For each author on the focal publication, we tabulated the number of articles published by that author cumulated from first publication to the year of the focal publication. We then took the average of the cumulative publications for all authors of the focal publication to control for the publishing experience of authors.

³ We did find, however, that more prior publications are indeed strongly correlated with the focal paper receiving more citations.

Number of authors. We controlled for the number of coauthors, as studies have shown an increasing trend of teamwork (Wuchty et al. 2007) and a positive correlation with citations (Singh and Fleming 2010). We counted the number of authors for each focal publication.

Impact factor. We also controlled for the impact factor of the journal in which the article was published, as articles published in higher-impact journals are more likely to be viewed and, hence, picked up. We calculated the impact factor using the Thomson Reuters method, defined as citations from research articles to the journal in the current year to items published in the previous two years, divided by the total number of scholarly items (these comprise articles, reviews, and proceedings papers) published in the journal in the previous two years.

Additionally, in the full regression specifications, we also included subfield fixed effects and *publication year* fixed effects.

Model Estimation

The findings that we observed are first represented graphically. We then performed further analyses using regression models to control for potentially confounding variables and to explore the variation of the effects across different contingencies. We used two regression models for our tests, along with a few robustness checks mentioned below.

The first model we employed was a negative binomial regression with number of *total cites* as the dependent variable since it is an over-dispersed count variable, and the independent variables and controls mentioned above. We chose negative binomial models instead of simple Poisson models to circumvent the assumption of equal mean and variance distribution to minimize estimation bias, as follows:

$$\begin{aligned} Total\ cites_i = & \beta_0 + \beta_1 \cdot avg\ frequency_i + \beta_2 \cdot \#\ of\ MeSHes_i + \beta_3 \cdot avg\ distance_i \\ & + \gamma \cdot Controls_i + \delta_i + \tau_i + \varepsilon_i \end{aligned}$$

where for publication i , β_1 and β_2 are the coefficients of interest for the competition for attention independent variables, β_3 is the coefficient of interest for the bias against novelty independent variable, δ_i is a dummy variable for the narrow subfield that the publication belongs to (thus incorporating subfield fixed effects), τ_i is its year of publication (thus incorporating publication-year fixed effects), and ε_i is the noise term.

The second model was a logistic regression with *top 1% of cites*, an indicator, as the dependent variable and independent variables and controls mentioned above:

$$\begin{aligned} \text{Top 1\% of cites}_i = & \beta_0 + \beta_1 \cdot \text{avg frequency}_i + \beta_2 \cdot \# \text{ of MeSHes}_i \\ & + \beta_3 \cdot \text{avg distance}_i + \gamma \cdot \text{Controls}_i + \tau_i + \varepsilon_i \end{aligned}$$

where for publication i , β_1 and β_2 are the coefficients of interest for the competition for attention independent variables, β_3 is the coefficient of interest for the bias against novelty independent variable, τ_i is its year of publication (thus incorporating publication-year fixed effects), and ε_i is the noise term. Note that we do not include subfield fixed effects here since the dependent variable is constructed at the subfield level.

Findings

Competition for Attention

Main effects. We first present our main findings (using the longest forward citation accumulation window of 15 years after publication) graphically. Figure 1 illustrates the relationship between competition for attention as operationalized using average frequency and idea recognition. We find that the number of forward cites and the probability of being in the top 1% (as well as the 95% confidence interval for both) fall in average frequency, as shown respectively in Figures 1A and 1B. Hence, the more a publication covers familiar topics, the

more it has to compete for attention, the less cites it will receive, and the less likely it is to become a breakthrough paper. This supports Hypothesis 1.

[Insert Figure 1 about here]

Our graphical evidence shows raw correlations between the dependent and independent variables and does not account for the control variables. However, our regression results in Tables 2 and 3, which ultimately include all controls and fixed effects, are reassuringly consistent with the plots. We find in Model 1 of Table 2 that a 10,000-unit increase in average frequency translates to a 9.3%⁴ significant decrease on forward cites. If we include all independent control variables and subfield as well as time fixed effects into the regression, as shown in Model 5, we find a 11.8% significant decrease in forward citations for a 10,000-unit increase in average frequency. The effect sizes are similar for a publication to be in the top 1% of forward citations using logistic analysis. Model 1 of Table 3 shows a 10.2%⁵ significant decrease in the odds of being in the top 1% of forward citations with a 10,000-unit increase in average frequency, while Model 5 shows a 11.8% significant decrease in the same odds of being in the top 1% of forward citations with a 10,000-unit increase in average frequency when accounting for all independent control variables and fixed effects. These regression results fully support our graphical evidence, in that articles obtain fewer citations on average and are less likely to become a highly cited breakthrough paper when they cover popular topics of current conversation. These regression results fully support our graphical evidence, in that articles obtain fewer citations on average and are less likely to become a highly cited breakthrough paper when they cover popular topics of current conversation.

[Insert Table 2 and 3 about here]

⁴ $e^{\text{coefficient}} - 1 = e^{-0.0971} - 1 = -0.0925$

⁵ $e^{\text{coefficient}} - 1 = e^{-0.108} - 1 = -0.1024$

Figure 2 plots the relationship between competition for attention as operationalized using the number of MeSHs and idea recognition. Our findings indicate a strong pattern of increasing cites and top 1% probability (and the 95% confidence interval) in the number of MeSHs, as shown respectively in Figures 2A and 2B. Thus, the more topics a publication covers, the more likely it can be found when searched and the more attention it attracts, which translates into more cites received and a higher likelihood of becoming a breakthrough paper.

[Insert Figure 2 about here]

Again, to ensure the robustness of our findings, we also ran regressions and found full support for the graphical evidence. We find in Model 2 of Table 2 that one additional MeSH keyword indexed on the publication translates to a 7.2% significant increase in forward citations.

There might be a concern that perhaps the increasing number of citations associated with a larger number of MeSH keywords might be due to an omitted variable – time – wherein over the years, papers have tended to include more MeSH keywords, and the average number of citations has also increased. While this would not address the frequency results, we did rerun our analysis with year fixed effects, and the results were unchanged. If we include all independent variables, control variables, and fixed effects into the regression, as shown in Model 5, we find a 4.4% significant increase in forward citations per one-unit increase in MeSH keyword. The effect sizes are even more pronounced for a publication to be in the top 1% of forward citations using logistic analysis. Model 2 of Table 3 shows a 10.6% significant increase in the odds of being in the top 1% of forward citations for one additional MeSH keyword indexed, while Model 5 shows an 9.2% significant increase in the same odds when accounting for all independent control variables and fixed effects. These regression results fully support our graphical evidence, in that articles obtain fewer citations on average and are less likely to become a highly cited

breakthrough paper when they cover popular topics of current conversation. Hence, we find evidence for the competition for attention mechanism.

Aside from focusing on mean regressions, we also investigated the dispersion of forward citations. We know from our findings above that the less competition for attention there is, the more likely a paper is to be picked up and cited. However, when articles focus on rarely discussed topics, we would expect a high potential for gains but also a high failure rate, since if a topic is too far from mainstream, it will be difficult for it to be recognized. This pattern was found in the data, as illustrated in Figure 3, which plots the standard deviation (and its 95% confidence interval) of the number of forward citations on quartiles of both measures of competition for attention.⁶

[Insert Figure 3 about here]

Variation of Effects. Given these results, we wanted to explore trends of how competition for attention may vary based on various factors. First, we explored how competition for attention trended throughout the three-decade span that our data covers. We divided our full sample into three subsamples according to the decade of publication: the 1970s, 1980s, and 1990s. Second, we separated the forward citation window into short-, medium-, and long-term windows. Our main results use the long-term window of 15 years, but we also investigated how competition for attention is linked to a short-term forward citation window of three years and a mid-term window of 10 years. Finally, we divided total forward citations into home field citations and foreign field citations. Home field citations are forward citations from publications in the same narrow subfield as the focal paper, while foreign field citations are forward citations from publications

⁶ We thank one of the referees for pointing us in this direction.

outside the same narrow subfield. Tables 4 to 6 respectively show all these variations for citation windows of 15, 10, and 3 years.

[Insert Table 4, 5, and 6 about here]

Model 1 in Tables 4, 5 and 6 show the full regression model on the full data sample using the total number of citations as the dependent variable. Comparing the effect sizes for average frequency of MeSH keywords in Table 4 for the 15-year window, Table 5 for the 10-year window, and finally Table 6 for the three-year window, we observe stronger effects for the shorter forward citation windows. Specifically, a 10,000-unit increase in average frequency translates to an 11.8% significant decrease on forward cites in the 15-year window, while the effects are stronger in the 10-year and 3-year windows with respectively a 12.7% and 15.5% significant decrease. These findings suggest that shortly after an article has been published, competition for attention, as measured by average frequency, is stronger, since the contributions of the article are still uncertain. As time passes, the article's contribution becomes settled, and the effect of competition for attention is weaker. When measuring competition for attention using the number of MeSH keywords, we observe different but less pronounced trends. The effect sizes are very similar between the 15-year and 10-year window with an additional keyword translating to a 4.4% significant increase in citations, while for the 3-year window the increase in citations is 3.8% and weaker.

To observe whether competition for attention has strengthened or weakened over time, Models 2 to 4 in Tables 4 depict the division of our data into, respectively, the 1990s, 1980s, and 1970s. We ran these regressions without time fixed effects, as it is precisely these time trends that we are exploring. The findings show that for both measures of competition for attention, the effects decrease over time, as they are weaker in the 1990s and stronger in the 1970s. For

instance, a 10,000-unit increase in average frequency translates to a 21.1% significant decrease on forward cites in the 1970s, whereas in 1990s the decreasing effect shrank to 11.1%. We posit that this weakening trend may be because fields have become more and more specialized (our data contains 118 narrow subfields in the 1970s, 154 in the 1980s, and 174 in the 1990s) even as science has expanded. Additionally, it may also be due to improved search tools through the decades, which enable more focused search. These trends are robust to the 10-year mid-term and 3-year short-term forward citation time windows, as evidenced in Tables 5 and 6.

Switching the dependent variable to the indicator variable of being in the top 1% of the citation distribution, we find similar trends in Table 7 as for the number of citations. First, when comparing the effect sizes contingent on the forward citation time window, we find stronger effects for the shorter window of 3 years (Models 1 to 3) than the longer 15-year window (Models 4 to 6). Second, when exploring time trends by decade, we also find that competition for attention weakens from the 1970s to the 1990s, as shown, respectively, in Models 1 to 3 and Models 4 to 6.

[Insert Table 7 about here]

Finally, we also contrasted forward citations from the same narrow subfield with those from outside the subfield in Models 5 and 6 of Table 4. We observe similar effect sizes for average frequency for both home and foreign citations, and slightly stronger effects on home citations for number of MeSHs – a 5.0% significant increase for home citations vs. a 3.7% significant increase for foreign citations. Since citing researchers in the home subfield know the subfield better, articles need to compete slightly more for attention when the citations are from the same subfield. It is also interesting to note that citations from foreign subfields depend more on signaling due to stronger information asymmetry in the foreign field, as the effect size for the

average cumulative publication of authors, the number of authors, and the impact factor of the journal—all signals of quality—are all positive and stronger for foreign citations than for home citations. These trends are also robust to the 10-year mid-term and 3-year short-term forward citation time windows, as shown in Tables 5 and 6.

Bias Against Novelty

Main effects. Using the same dataset and forward citations collected 15 years after publication, we also replicated previously documented results pertaining to the bias against novelty. For the entire population of published articles per year in the life sciences, we tabulated the number of co-occurrences of all pairwise combinations of MeSH keywords.

Figure 4 illustrates and documents the bias against novelty mechanism as operationalized using distance of recombination. As expected, citations and the top 1% of cites 15 years after publication decrease in average distance as compared to articles in the same field published in the same year (and their 95% confidence interval) (see Figures 3A and 3B). The more a publication recombines distant topics, the more novel the recombined ideas are, the less cites it will receive, and the less likely it is to become a breakthrough paper. Moreover, we replicated the finding that breakthrough papers tend to contain mostly conventional ideas sprinkled with atypical combinations (Uzzi et al. 2013). Operationalizing conventionality as the median distance and atypicality as the maximum distance of a paper, we found, as expected, that cites decrease in median distance, while increasing in maximum distance of the dyadic recombination used (see Figures 3C and 3D).⁷ The conventionality of small median recombination distance is recognized, but so is atypicality with large maximum recombination distance.

[Insert Figure 4 about here]

⁷ I.e., for all the MeSH pairs in a paper, find the MeSH pairs that have the highest distance and those that are at the median distance for that paper.

Model 3 in Tables 2 and 3 document the bias against novelty view where the dyadic recombination distance of MeSH keywords is negatively correlated with forward citations with high significance and with being top cited with high significance, respectively. Specifically, one additional unit in average dyadic distance between MeSH keywords on the publication translates to a 62.8% significant decrease in forward citations (model 3 of Table 2) and an 87.5% significant decrease in the odds of the publication being in the top 1% of forward cites (model 3 of Table 3). Thus, publications recombining more distant (or novel) ideas tend to be associated with lower forward citation counts on average or with a decrease in the likelihood of being top cited, consistent with our findings in Figures 3A and 3B.

All of the above results remain robust to combining the three independent variables, adding all control variables and time fixed effects, as shown in Models 4 and 5 in Tables 2 and 3. The findings are also robust to including heteroscedasticity robust standard errors. Model 5 of the two tables, respectively, show a 77.6% significant decrease in forward citations and a 95.3% significant decrease in the odds of the publication being in the top 1% of forward cites associated with one additional unit in average dyadic distance between MeSH keywords on the publication.

Variation of Effects. Similar to competition for attention, we explored trends and variations in bias against novelty contingent on the decade, the forward citation time window, and home versus foreign citations, as shown in Tables 4 to 7. In line with prior research, we find stronger effects of novelty in foreign citations since these foreign and distant subfields are more likely to accept a more diverse recombination of ideas, and stronger effects of bias against novelty for short-term recognition, as the article's contributions are still uncertain (Wang et al. 2017). Moreover, we find that bias against novelty strengthens over the decades from the 1970s to the 1990s. With the expansion of science and increased specialization into more subfields, the distance of recombination increases over time, and the bias against novelty effect may as well.

Competition for Attention and Bias Against Novelty

Empirically, our constructs for the processes of bias against novelty and competition for attention lend themselves to a simultaneous process. For instance, the less crowded a domain or the less common an idea is, the rarer its dyadic recombination with another idea is likely to be. Similarly, the more topics a publication spans, the more likely it is to produce something more qualitatively novel. Since creativity is often about novel recombinations of existing ideas, the more topics that are spanned, the greater the likelihood that some recombinations of these ideas are more novel. Hence, both cases illustrate that even if an article includes less common recombinations and suffers from its newness, its recognition can still be boosted by being published in a less crowded area.

Given these channels of action, one can reasonably expect both these mechanisms to be at work simultaneously. Thus, we also explored ways in which their joint action could influence idea recognition. Following, respectively, the competition for attention and bias against novelty mechanisms, we expected low distance and low frequency to be best, and high distance and high frequency to be worst, for idea recognition. We divided our sample into high and low average frequency and average distance from each measure's median, and plotted the probability of being a top 1% forward cited breakthrough paper 15 years after publication, conditional on distance of recombination and competition for attention in Figure 5. We observed the expected pattern where articles on less common topics and recombining ideas that are closer to one another are the most likely to be in the top 1%, suggesting that both the competition for attention and bias against novelty mechanisms are present. Conversely, articles on familiar topics and recombining more distant ideas are the least likely to be highly recognized, as they not only suffer from the bias against novelty but also have to compete more for attention (see Figure 5A). Similarly, using median splits of the number of MeSHs per publication, we also observed the highest top

1% probability of recognition for low distance and a high number of MeSHs (see Figure 5B).

Again, the likelihood of breakthrough increased when bias against novelty is low and the attraction of attention is high.

[Insert Figure 5 about here]

Additional robustness checks

In addition to the robustness checks mentioned above, we performed a few additional ones in our regression analysis to ensure the consistency of our findings. In the interest of conciseness, regression results for these robustness tests are not shown herein, but are available upon request from the corresponding author.

Narrow vs. Broad subfields. To ensure that our results are not sensitive to the Web of Science's subfield classifications, we also performed the same set of analyses using the broad subfield classification ($n = 16$) instead of the narrow classification ($n = 178$). This includes generating a new dependent variable indicating the top 1% of the citation distribution clustered by year of publication and broad subfield. All our results remain robust to this specification.

Different regression specifications. Given that the dependent variable tabulating the number of forward citations is non-negative and could be an over-dispersed count, we also used ordinary least squares models with robust standard errors. All our results using negative binomial specifications remain robust to the OLS specification (please refer to Tables A2 in the Appendix). Similarly, for the indicator dependent variable, we also ran probit regression models that returned robust and similar results to the logistic regression.

Discussion and Conclusion

Implications for the Literature

In this work, we enrich extant understanding of the phenomenon of idea recognition and diffusion—key drivers in the advancement of knowledge due to their cumulative nature (Furman and Stern 2011)—by introducing a new perspective, what we refer to as the competition for attention view. We contribute to the innovation literature on breakthrough recognition by introducing insights from the organizational and marketing literatures on how people, products, and ideas have to compete for the attention of the audience they are trying to address due to informational overload (Hannan and Carroll 1992; Hansen and Haas 2001; Iyer and Katona 2016; Ocasio 2011; Shen et al. 2015). This competitive view departs from most prior work on innovation, which has focused on cooperation and collaboration (Burt 2004; Fleming et al. 2007; Singh and Fleming 2010) as drivers of idea recognition, and is in line with the practice of differentiating one’s idea from other more common ideas, as incentivized by the priority-reward system in science (Merton 1957). Coining a term or being among the first to study a phenomenon or propose a theory enables the researcher to direct the scientific conversation and claim a domain, which translates into further usage and recognition.

Our findings call for new emphasis on the recombination of ideas and on the principle of competition when exploring the spread of ideas. In other words, we break away from the prevailing assumption that a novel idea is necessarily a rare one. Instead of only focusing on the single dimensional view of novelty when studying the spread of ideas, our work pinpoints the need to take a two-dimensional viewpoint where novelty and rarity drive different mechanisms. Analyzing three decades of publication data in the life sciences, we add a more nuanced view to the recognition and spread of ideas by focusing not only on how it relates to combinatorial novelty but also by introducing the perspective that articles compete for the attention of researchers who might build upon them.

The findings indicate a highly significant negative relationship between average frequency (competition for attention) and forward citations as well as with being a top-cited paper (recognition). These results, respectively, imply that publishing in areas of increasing popularity is associated with fewer forward citations and correlates with a decrease in the likelihood of having the 1% top-cited paper within the same narrow subfield and publication year. We also observed a highly significant positive relationship between the number of MeSH keywords describing a publication with forward citations and with a publication with being top cited. This is because the more indexed keywords facilitate discovery of the article for subsequent works to build onto and tend to increase attention to the article by subsequent works.

Furthermore, when exploring conditions under which these effects might vary, we find that competition for attention is stronger for the shorter citation time window, since shortly after an article has been published its contributions are still uncertain. As time passes, the article's contribution has settled, and the effect of competition for attention weakens. We also observe that the effects of competition for attention decreased over time from the 1970s to the 1990s. Finally, we find similar effect sizes for both home and foreign citations.

Our findings also enrich the literature on the spread of innovation and breakthrough ideas by mirroring the density dependence argument to help theorize the concurrent effects of bias against novelty and competition for attention (Hannan and Carroll 1992). Together, the two mechanisms mirror the interplay between legitimacy and competition from the density dependence argument onto the idea space. When new domains – whether industries or ideas – emerge, they are less crowded but tend to have limited legitimacy. There is less competition for attention but also more bias against this novel area. Conversely, once a domain becomes more crowded, it has gained legitimacy; hence, there is less bias against it, but competition for

attention increases. Thus, the density dependence argument and findings from our correlational empirical design are supportive of a simultaneous process.

Implications for Practitioners and Policymakers

The mechanism of competition for attention illustrates the common dilemma that many researchers, especially young ones, face concerning whether to choose to do research in a trendy or more remote area. The former choice may lead to faster or easier publications and more grants opportunities, as agencies and governments sometimes identify target areas for grant funding. By contrast, the latter choice may face more resistance in publishing but, as our findings illustrate, may be more likely to garner greater recognition and impact since there is more room for contributions. Consider how a biochemist at a leading U.S. research university explained his choice of a less crowded area of research: “I have to admit that there was also a certain lazy pleasure in it because you didn’t have to read a lot of papers.” However, publishing in remote areas is still risky, as seen in the increased variance in the dispersion of forward citations. Thus, there is a risk versus reward tradeoff that should be taken into account. Hence, our findings help researchers and managers, especially those in science-based and technology-intensive firms, decide how to choose the direction of their future research.

From managerial and policy standpoints that seek to justify and optimize private and public investment in science in search of the next breakthrough, our findings provide a new measure of how the rarity of an idea influences how it competes for the attention of future consumers of such ideas. Hence, it also potentially improves the accuracy in breakthrough prediction that policymakers and corporate lab managers can use in their investment decision-making process.

Limitations and Future Research

The empirical and theoretical limitations of this work stem from the cross-sectional nature of our current research design. Although theoretically sound, the empirical relationships we tested are correlational and might suffer from endogeneity issues even after controlling for factors known to influence idea recognition, such as the reputation and impact of the publication outlet and the number of coauthors available to promote the work (Fleming et al. 2007). Moreover, this cross-sectional view also constrains us from developing a dynamic understanding that takes into account the evolution of a field. Theoretically, we borrow from population ecology to infer simultaneity in the bias against novelty and competition for attention mechanisms; again, however, our cross-sectional tests limit us from tracing the process through which an idea is recognized.

For instance, one could posit in more depth about whether the two act simultaneously or sequentially in the overall process of idea recognition. One can see how a sequential process might be at play, with the competition for attention mechanism being an initial filter as individuals first search for articles in a given domain using keywords, and, once an appropriate article has been found, the bias against novelty mechanism acting only on those papers that pass through this filter. However, if the purely sequential process was the only one at play, it would have implied that papers in the high competition and low novelty combination should have received many fewer citations than those in the low competition and high novelty combination, as the publications in the former category would have been filtered out due to high competition. We do not see this stark pattern in the data, as the mean 15-year forward citation is 23.93 for the high competition and low novelty combination and 26.88 for the low competition and high novelty combination, implying that the sequential argument might not be the only one, and that there may be a strong simultaneous component as well. Hence, further research should examine each step separately to gain a clearer understanding of the process. This can also be done

qualitatively by interviewing researchers to appreciate when and how they consider the two mechanisms.

Having taken a first cross-sectional measurement of frequency and distance at the time of publication, future research can also explore in more depth how the dynamics of these features affect idea recognition. As domains evolve and greenfield spaces gain popularity and become more crowded, how do the effects of the bias against novelty and competition for attention channels change as a field matures? Does the effect of one become stronger or weaker as time passes?

It is also interesting to note that our empirical operationalization of the two mechanisms suggests that the attention view applies to single MeSH keywords, while novelty acts on pairs. Although the bias against novelty might have been expected to apply to single keywords as well, it appears that the effect of the competition for attention is strong enough to override and reverse that effect, as seen by outcome measures moving in the opposite direction than would be predicted by a bias against novelty measure applied at the single keyword level. This might be the case because when researchers search for and cite articles, they usually characterize the work by single keywords and cite them for a single idea. For instance, Einstein is cited for his theory of relativity, and Newton for his law of gravity. Researchers are probably much less likely to search for keyword pairs or higher order combinations. Thus, the effect of the competition for attention mechanism could be expected to be strongest at the single keyword level. In contrast, combinatorial novelty is manifested by the recombination of ideas (Fleming 2001; Henderson and Clark 1990; Weitzman 1998) or keywords. Arguably, its effect gets stronger (or at least does not decrease) as higher order combinations are introduced. Future work can hopefully further explore this intriguing symmetry of effects and substantiate the validity of our measures by generalizing our findings to other creative settings, such as patents or products.

Finally, in light of the mechanism of competition for attention that we found in the recognition of ideas, it is worth considering whether these mechanisms documented in the literature are comprehensive or, instead, what other mechanisms may also affect the recognition of breakthroughs and how they interact with one another. Hence, the innovation literature can gain a more thorough and in-depth understanding of the phenomenon of the recognition of ideas and breakthroughs by not only searching for new channels of action but also by tracing these processes and the dynamics around their evolution.

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Variable	Observation	Mean	Std. Dev.	Min	Max
publication year	5,300,029	1988.033	8.034179	1970	1999
total cites (15yr)	5,300,029	26.98885	78.01378	0	49299
total cites (10yr)	5,300,029	22.57974	57.42935	0	30330
total cites (3yr)	5,300,029	8.156929	17.84104	0	3969
top1% of cites (15yr)	5,300,029	0.0099428	0.0992165	0	1
top1% of cites (10yr)	5,300,029	0.0099447	0.0992258	0	1
top1% of cites (3yr)	5,300,029	0.0099543	0.0992734	0	1
home cites (15yr)	5,300,029	14.46142	39.43114	0	31166
home cites (10yr)	5,300,029	12.18305	30.57669	0	19288
home cites (3yr)	5,300,029	4.520233	9.699633	0	2199
foreign cites (15yr)	5,300,029	12.52743	52.71717	0	39139
foreign cites (10yr)	5,300,029	10.39669	37.24478	0	15828
foreign cites (3yr)	5,300,029	3.636696	11.72168	0	3550
avg frequency(/10k)	5,232,299	2.900894	1.953521	0.0001	16.06245
# of MeSHs	5,232,299	11.5193	4.393472	1	53
average distance	5,230,303	0.1759706	0.1228729	0.0000263	1
median distance	5,230,303	0.0637036	0.112808	0.0000149	1
maximum distance	5,230,303	0.8704594	0.276203	0.0000263	1
minimum distance	5,230,303	0.0020553	0.0246364	0.00000776	1
avg cumulative pubs	5,160,163	35.01917	39.43043	1	1361
# of authors	5,300,029	3.609467	2.397941	1	394
impact factor	5,149,805	0.5902668	1.877485	0	70.5

Table 1.

This table shows the descriptive statistics for all variables in our sample of ~5.3M articles in the life sciences.

Note: The variation in the number of observations across the variables was due to missing data on those variables.

total cites (15yr)	Model 1	Model 2	Model 3	Model 4	Model 5
avg frequency(/10k)	-0.0971*** (0.000702)			-0.0980*** (0.000920)	-0.126*** (0.000967)
# of MeSHs		0.0698*** (0.000301)		0.0591*** (0.000312)	0.0430*** (0.000312)
avg distance			-0.990*** (0.00984)	-1.573*** (0.0127)	-1.495*** (0.0111)
avg cumulative pubs					0.00388*** (0.0000348)
# of authors					0.0602*** (0.000554)
impact factor					0.143*** (0.000764)
Constant	3.560*** (0.00244)	2.444*** (0.00428)	3.464*** (0.00218)	3.106*** (0.00707)	2.672*** (0.00964)
L _{nl} alpha					
Constant	0.359*** (0.00119)	0.325*** (0.00146)	0.370*** (0.00122)	0.299*** (0.00136)	0.224*** (0.00150)
subfield fe	yes	yes	yes	yes	yes
time fe					yes
N	5232299	5232299	5230303	5230303	5050334
Log lik.	22264426.0	22153207.3	22294057.4	22063798.2	21035192.2

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 2.

This table shows negative binomial regression models with narrow subfield fixed effects. The dependent variable for all models are the forward citations each article garners up to 15 years after its publication. The independent variables are: (a) in Models 1 and 2, respectively, the average frequency of all MeSH keywords and the total number of MeSH keywords in an article as measures of competition for attention; (b) in Model 3, the average distance between all dyads of MeSH keywords in an article as a measure of novelty; (c) in Model 4, all measures of competition for attention and novelty; and (d) in Model 5, all measures, controlling for the number of authors in the article, the average number of cumulative publications for authors of the article, the journal impact factor, and time fixed effects.

top 1% of cites (15yr)	Model 1	Model 2	Model 3	Model 4	Model 5
avg frequency(/10k)	-0.108*** (0.00244)			-0.133*** (0.00301)	-0.126*** (0.00361)
# of MeSHs		0.101*** (0.000891)		0.0936*** (0.000938)	0.0884*** (0.00116)
avg distance			-2.077*** (0.0414)	-3.237*** (0.0508)	-3.048*** (0.0539)
avg cumulative pubs					0.00576*** (0.0000639)
# of authors					0.0779*** (0.00286)
impact factor					0.143*** (0.00122)
constant	-4.303*** (0.00758)	-5.861*** (0.0130)	-4.260*** (0.00760)	-4.892*** (0.0191)	-5.478*** (0.0474)
times fe					yes
N	5232299	5232299	5230303	5230303	5050334
Log lik.	-291491.0	-286490.1	-291050.8	-283608.6	-260344.8

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 3.

This table shows logistic regression models. The dependent variable for all models are a dummy variable of whether the 15-year cumulated forward citations of the article is in the top 1% of the citation distribution clustered by publication year and narrow subfield. Given that the dependent variable is constructed at the subfield level, we do not include subfield fixed effects. The independent variables are: (a) in Models 1 and 2, respectively, the average frequency of all MeSH keywords and the total number of MeSH keywords in an article as measures of competition for attention; (b) in Model 3, the average distance between all dyads of MeSH keywords in an article as a measure of novelty; (c) in Model 4, all measures of competition for attention and novelty; and (d) in Model 5, all measures, controlling for the number of authors in the article, the average number of cumulative publications for authors of the article, the journal impact factor, and time fixed effects.

cites (15yr)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	total cites	total cites (90s)	total cites (80s)	total cites (70s)	home cites	foreign cites
avg frequency(/10k)	-0.126*** (0.000967)	-0.118*** (0.00113)	-0.176*** (0.00175)	-0.246*** (0.00482)	-0.127*** (0.00088)	-0.126*** (0.00141)
# of MeSHs	0.0430*** (0.000312)	0.0304*** (0.00040)	0.0584*** (0.00071)	0.0514*** (0.00088)	0.0485*** (0.00031)	0.0367*** (0.00041)
avg distance	-1.495*** (0.0111)	-1.819*** (0.01590)	-1.521*** (0.01870)	-1.381*** (0.02920)	-1.819*** (0.01150)	-1.131*** (0.01460)
avg cumulative pubs	0.00388*** (0.0000348)	0.00337*** (0.00004)	0.00474*** (0.00008)	0.00436*** (0.00011)	0.00332*** (0.00003)	0.00451*** (0.00005)
# of authors	0.0602*** (0.000554)	0.0524*** (0.00060)	0.0849*** (0.00123)	0.119*** (0.00251)	0.0500*** (0.00057)	0.0719*** (0.00073)
impact factor	0.143*** (0.000764)	0.0771*** (0.00045)	27.44*** (1.23800)	53.14*** (3.59400)	0.125*** (0.00084)	0.159*** (0.00094)
constant	2.672*** (0.00964)	3.147*** (0.00957)	2.803*** (0.01130)	2.667*** (0.02880)	1.912*** (0.00962)	2.036*** (0.01280)
lnalpha constant	0.224*** (0.00150)	0.188*** (0.00165)	0.284*** (0.00290)	0.267*** (0.00484)	0.425*** (0.00134)	0.606*** (0.00174)
subfield fe	yes	yes	yes	yes	yes	yes
time fe	yes				yes	yes
N	5050334	2541121	1590997	918216	5050334	5050334
Log lik.	-21035192.2	-10803361.2	-6555584.4	-3698690.1	-17872506.8	-16765801.7

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 4.

This table shows negative binomial regression models with narrow subfield fixed effects. The dependent variables for all models are forward citations with the *15-year window* after publication with (a) total number of cites in Model 1; (b) total number of cites for the 1990s, 1980s, and 1970s in Models 2 to 4; (c) the number of home cites in Model 5; and (d) the number of foreign cites in Model 6. The independent variables are all measures of competition for attention and bias against novelty, controlling for the number of authors in the article, the average number of cumulative publications for authors of the article, the journal impact factor, and time fixed effects.

cites (10yr)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	total cites	total cites (90s)	total cites (80s)	total cites (70s)	home cites	foreign cites
avg frequency(/10k)	-0.136*** (0.000873)	-0.119*** (0.00102)	-0.194*** (0.00174)	-0.253*** (0.00294)	-0.138*** (0.000830)	-0.134*** (0.00125)
# of MeSHs	0.0427*** (0.000270)	0.0308*** (0.000361)	0.0576*** (0.000619)	0.0507*** (0.000569)	0.0478*** (0.000279)	0.0367*** (0.000349)
avg distance	-1.607*** (0.00964)	-1.875*** (0.0141)	-1.666*** (0.0172)	-1.444*** (0.0205)	-1.924*** (0.0105)	-1.248*** (0.0121)
avg cumulative pubs	0.00415*** (0.0000334)	0.00357*** (0.0000414)	0.00518*** (0.0000730)	0.00472*** (0.0000899)	0.00355*** (0.0000326)	0.00481*** (0.0000453)
# of authors	0.0627*** (0.000513)	0.0539*** (0.000577)	0.0895*** (0.00112)	0.126*** (0.00173)	0.0521*** (0.000528)	0.0751*** (0.000684)
impact factor	0.142*** (0.000762)	0.0967*** (0.000458)	27.20*** (1.274)	54.60*** (3.469)	0.124*** (0.000842)	0.159*** (0.000933)
constant	2.447*** (0.00859)	2.960*** (0.00833)	2.616*** (0.0103)	2.442*** (0.0165)	1.693*** (0.00870)	1.805*** (0.0113)
lnalpha constant	0.212*** (0.00130)	0.167*** (0.00159)	0.274*** (0.00265)	0.225*** (0.00331)	0.410*** (0.00124)	0.605*** (0.00148)
subfield fe	yes	yes	yes	yes	yes	yes
time fe	yes				yes	yes
N	5050334	2541121	1590997	918216	5050334	5050334
Log lik.	-20112742.1	-10418975.0	-6187641.7	-3499277.0	-17015481.4	-15864243.2

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 5.

This table shows negative binomial regression models with narrow subfield fixed effects. The dependent variables for all models are forward citations with the *10-year window* after publication with (a) total number of cites in Model 1; (b) total number of cites for the 1990s, 1980s, and 1970s in Models 2 to 4; (c) the number of home cites in Model 5; and (d) the number of foreign cites in Model 6. The independent variables are all measures of competition for attention and bias against novelty, controlling for the number of authors in the article, the average number of cumulative publications for the authors of the article, the journal impact factor, and time fixed effects.

cites (3yr)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	total cites	total cites (90s)	total cites (80s)	total cites (70s)	home cites	foreign cites
avg frequency(/10k)	-0.168*** (0.000727)	-0.150*** (0.000846)	-0.235*** (0.00152)	-0.301*** (0.00176)	-0.173*** (0.000718)	-0.167*** (0.00101)
# of MeSHs	0.0376*** (0.000208)	0.0281*** (0.000298)	0.0509*** (0.000447)	0.0438*** (0.000367)	0.0416*** (0.000217)	0.0331*** (0.000284)
avg distance	-1.902*** (0.0078)	-2.266*** (0.0123)	-1.924*** (0.0137)	-1.707*** (0.0145)	-2.185*** (0.00850)	-1.582*** (0.0102)
avg cumulative pubs	0.00473*** (0.0000293)	0.00413*** (0.0000375)	0.00565*** (0.0000624)	0.00527*** (0.0000712)	0.00399*** (0.0000288)	0.00550*** (0.0000397)
# of authors	0.0685*** (0.000435)	0.0582*** (0.000534)	0.0961*** (0.000859)	0.132*** (0.00115)	0.0564*** (0.000429)	0.0836*** (0.000613)
impact factor	0.157*** (0.000721)	0.106*** (0.000417)	24.10*** (1.243)	51.28*** (3.267)	0.140*** (0.000824)	0.173*** (0.000825)
constant	1.609*** (0.00709)	2.056*** (0.00622)	1.777*** (0.00808)	1.604*** (0.00772)	0.893*** (0.00741)	0.930*** (0.00924)
lnalpha constant	0.230*** (0.00116)	0.229*** (0.00166)	0.268*** (0.00212)	0.162*** (0.00227)	0.404*** (0.00119)	0.685*** (0.00148)
subfield fe	yes	yes	yes	yes	yes	yes
time fe	yes				yes	yes
N	5050334	2541121	1590997	918216	5050334	5050334
Log lik.	-15112118.9	-7834514.9	-4643349.3	-2629650.8	-12396985.8	-11059971.6

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 6.

This table shows negative binomial regression models with narrow subfield fixed effects. The dependent variables for all models are forward citations with the 3-year window after publication with (a) the total number of cites in Model 1; (b) total number of cites for 1990s, 1980s, and 1970s in Models 2 to 4; (c) number of home cites in Model 5, and (d) number of foreign cites in Model 6. The independent variables are all measures of competition for attention and bias against novelty while controlling for the number of authors in the article, the average number of cumulative publications for authors of the article, the journal impact factor and time fixed effects.

top 1% of cites	Model 1 15 yr - 90s	Model 2 15 yr - 80s	Model 3 15 yr - 70s	Model 4 3 yr - 90s	Model 5 3 yr - 80s	Model 6 3 yr - 70s
avg frequency(/10k)	-0.0877*** (0.00407)	-0.283*** (0.00704)	-0.319*** (0.0126)	-0.133*** (0.00412)	-0.366*** (0.00716)	-0.442*** (0.0130)
# of MeSHs	0.0562*** (0.00156)	0.120*** (0.00223)	0.0966*** (0.00201)	0.0632*** (0.00153)	0.127*** (0.00220)	0.0943*** (0.00199)
avg distance	-3.837*** (0.0839)	-3.013*** (0.0883)	-2.328*** (0.111)	-5.234*** (0.0874)	-4.416*** (0.0945)	-3.807*** (0.123)
avg cumulative pubs	0.00493*** (0.0000776)	0.00630*** (0.000132)	0.00651*** (0.000195)	0.00515*** (0.0000789)	0.00715*** (0.000135)	0.00761*** (0.000213)
# of authors	0.0594*** (0.00300)	0.145*** (0.00350)	0.177*** (0.00576)	0.0681*** (0.00309)	0.177*** (0.00342)	0.227*** (0.00571)
impact factor	0.118*** (0.00108)	2.038*** (0.271)	9.835*** (1.138)	0.125*** (0.00108)	1.599*** (0.227)	11.72*** (1.069)
constant	-5.225*** (0.0329)	-5.585*** (0.0399)	-5.690*** (0.0479)	-5.064*** (0.0316)	-5.448*** (0.0378)	-5.461*** (0.0460)
times fe	yes	yes	yes	yes	yes	yes
N	2541121	1590997	918216	2541121	1590997	918216
Log lik.	-130050.0	-82953.2	-47235.1	-128098.1	-81297.6	-46259.2

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 7.

This table shows logistic regression models. The dependent variable for all models are a dummy variable of whether the cumulated forward citations of the article is in the top 1% of the citation distribution clustered by publication year and narrow subfield with the (a) 15-year window in Models 1 to 3, and (b) 3-year window in Models 4 to 6. Given that the dependent variable is constructed at the subfield level, we do not include subfield fixed effects. The independent variables are all measures of competition for attention and bias against novelty while controlling for the number of authors in the article, the average number of cumulative publications for authors of the article, the journal impact factor, and time fixed effects.

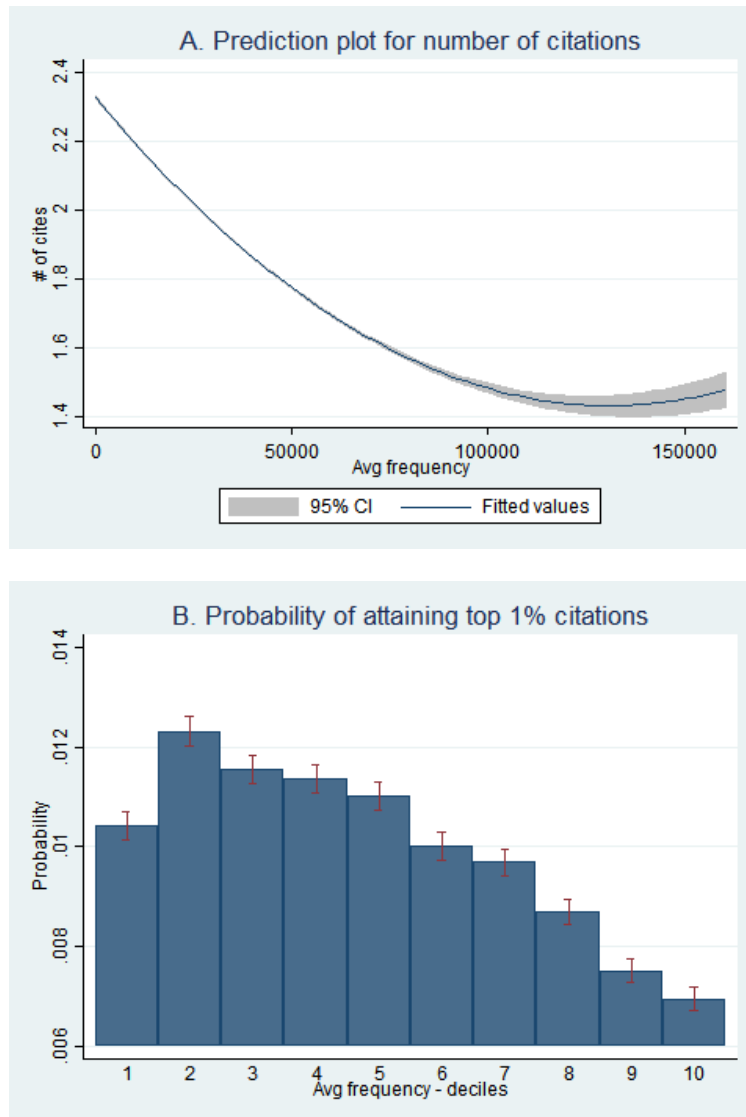


Figure 1. Competition for attention operationalized using average frequency. (A) The total number of forward citations 15 years after publication (and the 95% confidence interval) decrease as the average frequency of MeSH keywords used in the publication increase. (B) The probability of attaining the top 1% of cites 15 years after publication (and the 95% confidence interval) as compared to articles in the same field and published in the same year also decrease in average frequency. The more a publication covers familiar topics and the more it has to compete for attention, the fewer cites it will receive and the less likely it is to become a breakthrough paper.

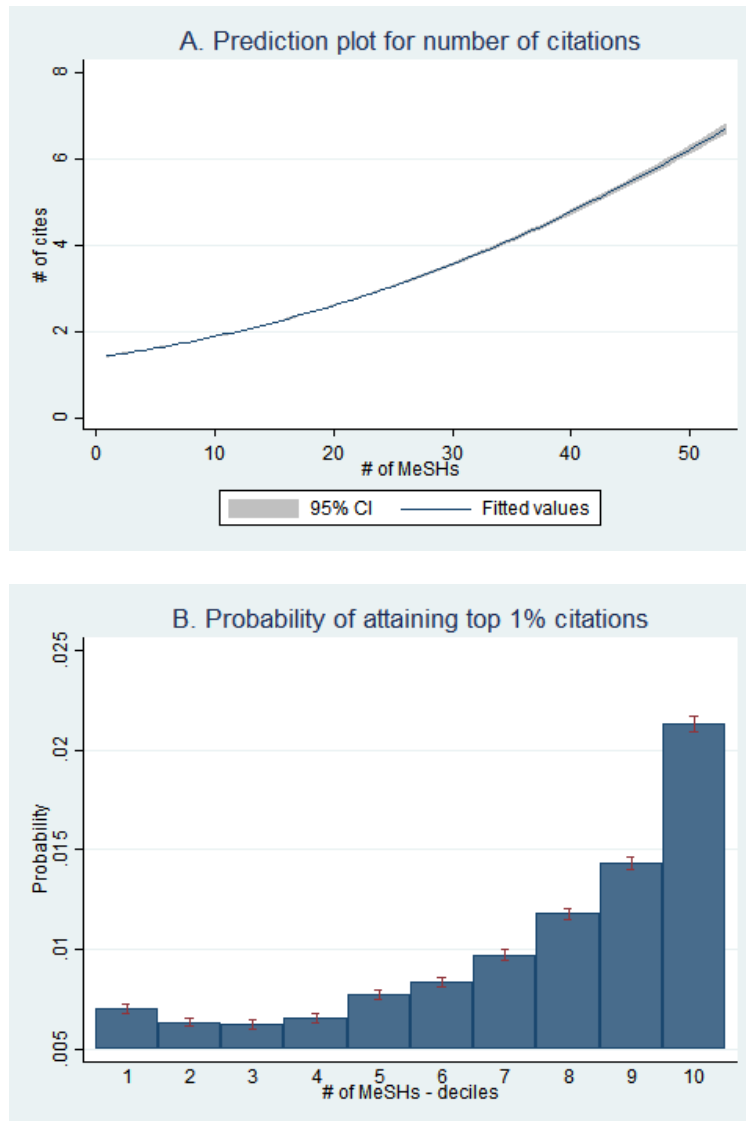


Figure 2. Competition for attention operationalized using number of MeSHs. (A) The total number of forward citations 15 years after publication (and the 95% confidence interval) increase in the number of MeSH keywords used in the publication. (B) The probability of attaining the top 1% of cites 15 years after publication (and the 95% confidence interval) as compared to articles in the same field and published in the same year also increase in the number of MeSHs. The more topics a publication covers, the more likely it is to be found when searched, the more cites it will receive, and the more likely it is to become a breakthrough paper.

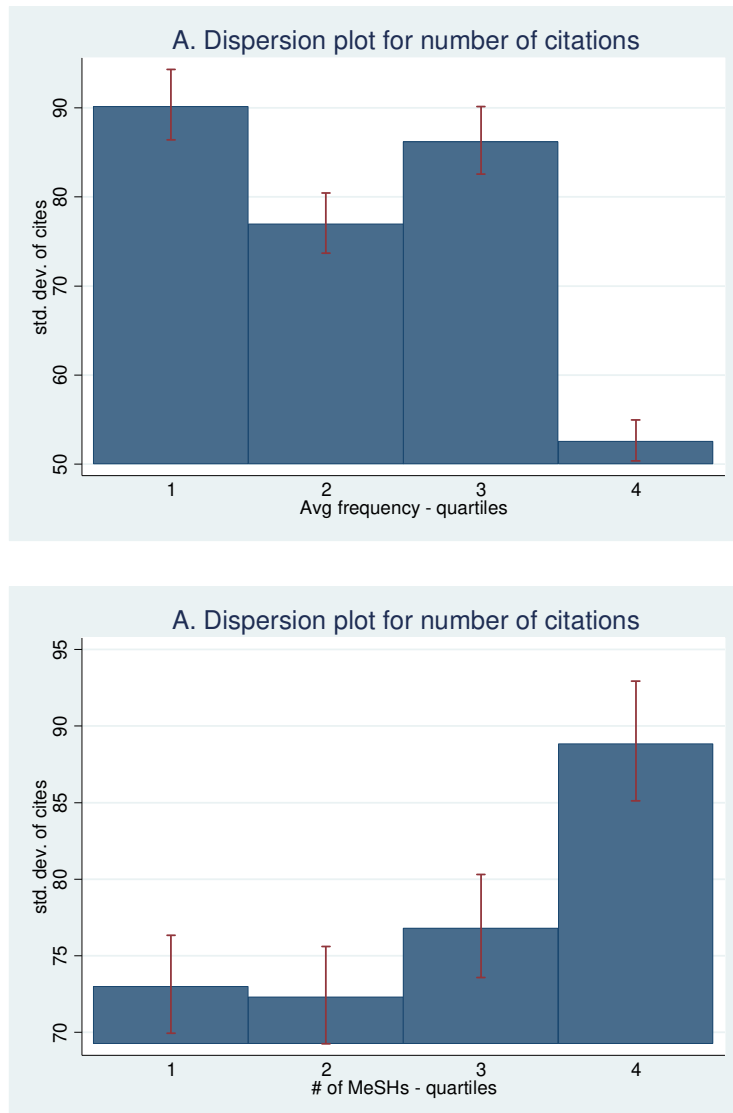


Figure 3. Dispersion (depicted using the standard deviation of the number of citations) quartile plots for competition for attention operationalized using average frequency and number of MeSHs. (A) Dispersion for the total number of forward citations 15 years after publication (and the 95% confidence interval) decrease as the average frequency of MeSH keywords used in the publication increase. (B) Dispersion for the total number of forward citations 15 years after publication (and the 95% confidence interval) decrease in the number of MeSH keywords used in the publication. Greater competition for attention (high average frequency or low # of MeSHs) is associated with greater uncertainty in idea recognition, as measured by the number of forward citations.

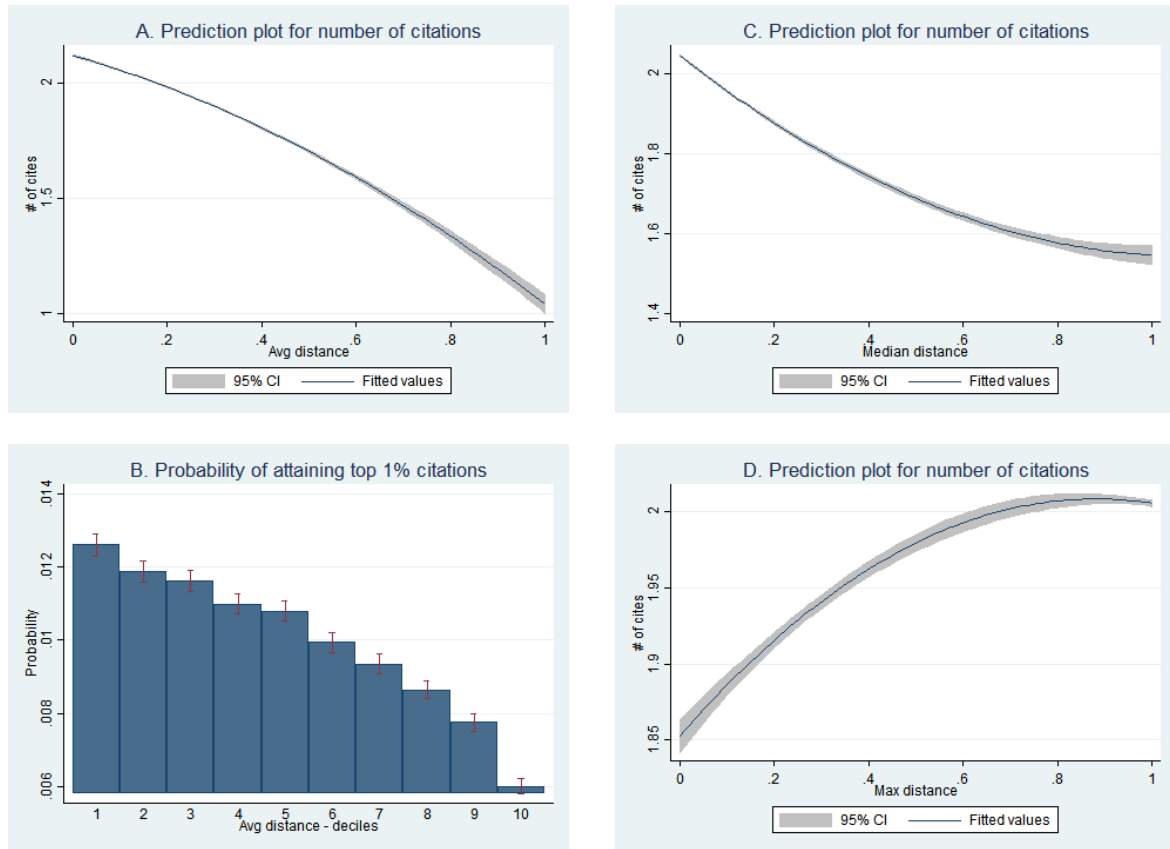


Figure 4. Bias against novelty is operationalized using distance of recombination. (A) The total number of forward citations 15 years after publication (and the 95% confidence interval) decrease in the average distance of dyadic recombination used in the publication. (B) The probability of attaining the top 1% of cites 15 years after publication (and the 95% confidence interval) as compared to articles in the same field and published in the same year also decrease in average distance. The more a publication recombines distant topics, the more novel the recombined ideas, and the less cites it will receive and the less likely it is to become a breakthrough paper. (C & D) The total number of forward citations 15 years after publication (and the 95% confidence interval) decrease in the median distance and increase in the maximum distance of dyadic recombination used in the publication. The conventionality of small median recombination distance is recognized, but so is atypicality with large maximum recombination distance.

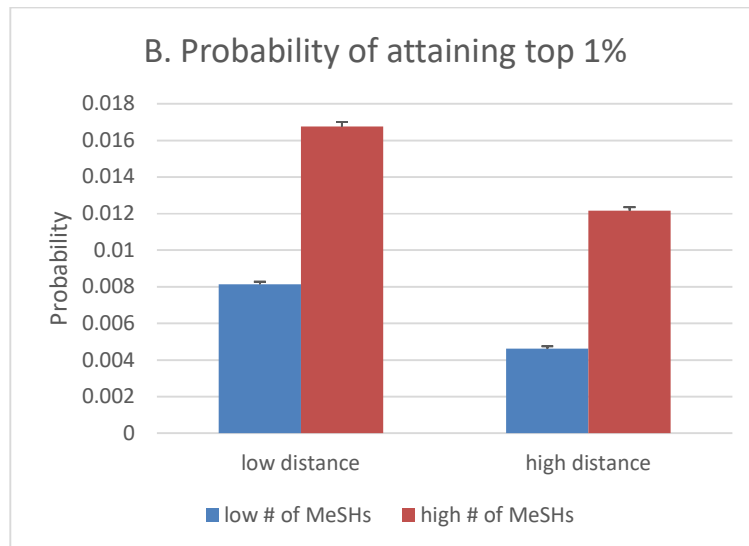
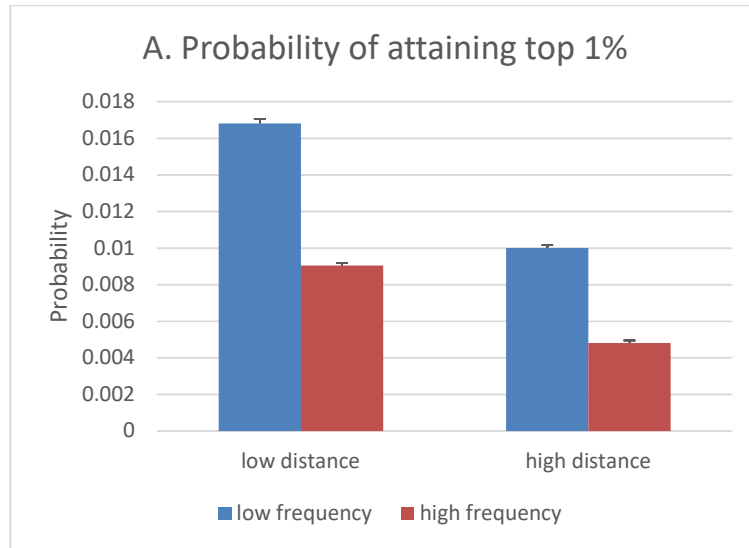


Figure 5. The probability of a breakthrough paper, conditional on the distance of recombination and competition for attention. Competition for attention is operationalized using (A) the average frequency of MeSH keywords and (B) the number of MeSH keywords. Both the competition-for-attention channels and bias against novelty are present, as articles covering most common topics (or with the least number of MeSHs) that recombine the most distant ideas from one another are the least likely to be in the top 1% of cites 15 years after publication.

	publication year	total cites (15yr)	total cites (3yr)	top1% of cites (15yr)	top1% of cites (3yr)	avg frequency (/10k)	# of MeSHs
publication year	1						
total cites (15yr)	0.0302	1					
# of cites (3yr)	0.0587	0.7517	1				
top1% of cites (15yr)	0.001	0.4902	0.4954	1			
top1% of cites (3yr)	0.0015	0.4267	0.5641	0.6266	1		
avg frequency (/10k)	0.3732	-0.0596	-0.0933	-0.0182	-0.0221	1	
# of MeSHs	0.0979	0.1141	0.1599	0.0505	0.0554	-0.2459	1
avg distance	-0.057	-0.0393	-0.0625	-0.0225	-0.03	-0.3957	-0.0025
median distance	-0.07	-0.0293	-0.0436	-0.0144	-0.0185	-0.3472	-0.1075
maximum distance	0.0173	0.0115	0.0088	-0.0031	-0.007	-0.2774	0.3547
minimum distance	-0.0316	-0.0124	-0.0161	-0.004	-0.005	-0.1057	-0.1276
avg cumulative pubs	0.1769	0.0513	0.0795	0.0356	0.039	0.1219	0.0381
# of authors	0.2483	0.0908	0.1352	0.0504	0.0599	0.0805	0.2306
impact factor	0.3658	0.1357	0.2389	0.0749	0.0857	0.0313	0.1378
	avg distance	median distance	max distance	min distance	avg cumulative pubs	# of authors	impact factor
avg distance	1						
median distance	0.8047	1					
maximum distance	0.4856	0.1835	1				
minimum distance	0.2493	0.3434	-0.0092	1			
avg cumulative pubs	-0.083	-0.0719	-0.0488	-0.0251	1		
# of authors	-0.0808	-0.0916	0.0705	-0.0358	0.0336	1	
impact factor	-0.0336	-0.0327	0.0149	-0.0094	0.091	0.1331	1

Table A1.

The correlation for major variables in our sample of ~5.3M articles in the life sciences.

total cites (15yr)	Model 1	Model 2	Model 3	Model 4	Model 5
avg frequency(/10k)	-1.542*** (0.0186)			-1.424*** (0.0207)	-2.058*** (0.0227)
# of MeSHs		1.893*** (0.0078)		1.752*** (0.0080)	1.316*** (0.0084)
avg distance			-26.75*** (0.2800)	-34.84*** (0.3020)	-31.91*** (0.3000)
avg cumulative pubs					0.0749*** (0.0009)
# of authors					1.990*** (0.0146)
impact factor					6.139*** (0.0220)
constant	31.48*** (0.0637)	5.199*** (0.0956)	31.72*** (0.0598)	17.09*** (0.1500)	6.080*** (0.3330)
subfield fe	yes	yes	yes	yes	yes
time fe					yes
N	5232299	5232299	5230303	5230303	5050334
R-sq	0.0206	0.0303	0.021	0.0329	0.0574

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table A2.

This table shows OLS regression models with narrow subfield fixed effects. The dependent variable for all models are the forward citations each article garners up to 15 years after its publication. The independent variables are: (a) in Models 1 and 2, respectively, the average frequency of all MeSH keywords and the total number of MeSH keywords in an article as measures of competition for attention; (b) in Model 3, the average distance between all dyads of MeSH keywords in an article as a measure of novelty; (c) in Model 4, all measures of competition for attention and novelty; and (d) in Model 5, all measures, controlling for the number of authors in the article, the average number of cumulative publications for authors of the article, the journal impact factor, and time fixed effects.