Article

The pivot penalty in research

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Scientists and inventors set the direction of their work amid evolving questions, opportunities and challenges, yet the understanding of pivots between research areas and their outcomes remains limited[1–5]. Theories of creative search highlight the potential benefits of exploration but also emphasize difficulties in moving beyond one's expertise[6–14]. Here we introduce a measurement framework to quantify how far researchers move from their existing work, and apply it to millions of papers and patents. We find a pervasive 'pivot penalty', in which the impact of new research steeply declines the further a researcher moves from their previous work. The pivot penalty applies nearly universally across science and patenting, and has been growing in magnitude over the past five decades. Larger pivots further exhibit weak engagement with established mixtures of prior knowledge, lower publication success rates and less market impact. Unexpected shocks to the research landscape, which may push researchers away from existing areas or pull them into new ones, further demonstrate substantial pivot penalties, including in the context of the COVID-19 pandemic. The pivot penalty generalizes across fields, career stage, productivity, collaboration and funding contexts, highlighting both the breadth and depth of the adaptive challenge. Overall, the findings point to large and increasing challenges in effectively adapting to new opportunities and threats, with implications for individual researchers, research organizations, science policy and the capacity of science and society as a whole to confront emergent demands.

Science has been described as an endless frontier[1,3,15,16]. New opportunities and challenges continuously emerge, from synthetic biology or climate change to the COVID-19 pandemic, and researchers and research organizations must consider adapting their research portfolios to address these emergent demands[4,5,17–19]. Adaptability is thus crucial for scientific and technological progress[1,3,15], and adaptive success or failure can underpin the relative progress or collapse of organizations, economic regions and societies[1,3,15,16,20,21].

The adaptability of research streams hinges on researchers, who must regularly consider the direction of their work and their potential to engage with new areas. Researchers face consequential choices across large or small changes in their research directions, but the degree to which research directions are adaptable depends on fundamental trade-offs and unknowns. On one hand, shifts in research may be difficult[14], because the specialization of expertise[12,13,22], the design of funding systems[23,24] and the nature of research incentives, culture and communities[7,25–27] may all limit the capacity of a given individual to respond effectively to changing opportunities and demands[28–32]. On the other hand, the value of novelty[8,33,34] and exploration[6,9,35] in creative search suggests that moving further from one's usual research area might be particularly fruitful[10,11,14,36], and new entrants or 'outsiders' to a given area are sometimes thought to be especially capable of transformative ideas[7,37]. Indeed, a researcher who continues to exploit an existing direction may face diminishing returns and miss opportunities afforded in other areas[6,38]. Exploring new areas might be risky, but it may also be more likely to produce high-impact insights.

Here we study the adaptability of scientists and inventors, and examine the outcomes when researchers work in areas nearer or further from their existing research portfolio. We introduce a measurement framework for research pivots and then study adaptability in both general and specific settings. We first apply the measurement framework at high scale across scientific and technological domains, studying millions of scientific articles indexed by Dimensions from 1970 to 2020 and US patents granted from 1985 to 2020 (Supplementary sections 1.1–2). The core finding is that there is a substantial pivot penalty, meaning that the further a researcher moves from their previous work, the worse the research performs in terms of citation impact, publication success and a host of other outcomes. The negative effects of pivoting occur for individual researchers, across wide-ranging fields of inquiry, and have been increasing over time. We then evaluate the pivot penalty in terms of canonical conceptual frameworks, and investigate potential mechanisms, drawing on ideas of reputation and audience[32,39–41], as well as creativity frameworks in the production of new ideas[6,8,12]. Finally, we turn to case studies of substantial interest to science and in which exogenous events can elicit research pivots. We study 'push' events, in which existing knowledge is revealed to be incorrect or unreliable, pushing researchers away from their previous research streams. We also study a 'pull' event—the COVID-19 pandemic—that drew researchers into

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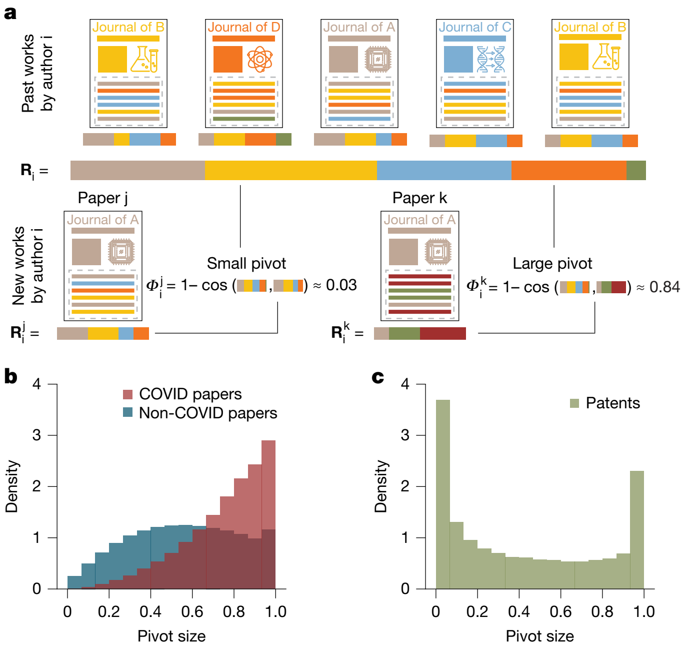

Fig. 1 | Quantifying research pivots. a, The pivot measure compares a focal work against previous works by the same researcher. An increasing value on the [0,1] interval indicates a larger pivot from the researcher's previous work. In the sciences, journals are used to define research areas (pictured); in patenting, technology classes are used. **b**, The distribution of author pivots in 2020 (n = 8.32 million author-by-paper observations) is dispersed across the [0, 1] interval. **c**, The distribution of inventor pivots in 2020 (n = 166,000 inventor-by-patent observations) is dispersed across the [0, 1] interval and is bimodal. COVID-19 papers (**b**) showed higher median pivots than other papers in 2020. Fig. 1a, icons adapted from the Noun Project (https://thenounproject.com).

an important new research area. We find that despite the wide-ranging nature of these events, researchers pivot to an unusually large degree after these events, and the pivot penalty persists in each case. The pandemic also allows us to examine a consequential, society-scale event and the capacity of science as a whole to address the new research demands. We conclude with a discussion about the implications of these findings for researchers, research organizations and science policy.

Measurement framework

To quantify pivots for researchers, we calculated a cosine-similarity metric that measures the extent to which a given new work departs from a researcher's previous body of work (Fig. 1a and Pivot size in the Methods). For papers, we considered the referenced journals, comparing the focal work with the previous body of work for that author. The pivot measure, Φ, varies on the [0,1] interval. It takes the value 0 (zero pivot) if the focal paper draws on exactly the same distribution of journals as the author's previous work, and takes the value 1 (full pivot) if the focal paper draws on an entirely different set of journals. In the patent context, for which journal information is not available, we use technological field codes to measure pivots (see Pivot size and Supplementary section 2.2 for details and alternative constructions of the pivot measure).

Figure 1 shows the distribution of pivoting behaviour, focusing on the year 2020. Pivoting values ranged across the [0,1] interval in both the science and patenting contexts, indicating that pivoting is prevalent for both scientists and inventors (Fig. 1b,c). We also observed a sharp increase in pivot size for research related to COVID-19, in that scientists who engaged with COVID-19 exhibited unusually large pivots; whereas papers not related to COVID-19 in 2020 have a median of $\overline{\Phi} = 0.60$, COVID-19 papers present a substantially larger median pivot size of $\overline{\Phi} = 0.82$ ($P < 0.001$, chi-squared test for median differences). The variable nature of pivot size is particularly prominent in patenting, for which we observed a bimodal distribution (Fig. 1c), showing a tendency for both small and large jumps. Supplementary section S2.2 provides further analysis of these patterns, demonstrates their robustness across alternative pivot measures and offers specific examples of pivoting.

The pivot penalty

When scientists and inventors shift away from their earlier research, a central question is how impactful their new work becomes. We first considered 25.8 million papers published from 1970 to 2015 across 154 fields. To quantify impact, we calculated a binary, paper-level indicator for whether a given work was in the upper 5% of citations received in its field and publication year[42]. In Fig. 2a, the data are presented as binned scatterplots, with papers grouped by pivot size into 20 equally sized groups and showing the mean rate of high-impact papers for each group (see Binned scatterplots in the Methods). Figure 2a reveals a striking fact: across the whole of science, papers with larger average pivots have a systematically lower propensity for high impact. Indeed, we observed a large, monotonic decrease in the average hit rate as the pivot size rises. The lowest-pivot work had high impact 7.4% of the time, which is 48% higher than the baseline rate ($P < 0.001$ in one sample t-test), whereas the highest-pivot work had high impact only 2.2% of the time, which is a 56% reduction from the baseline ($P < 0.001$). Figure 2b normalizes impact for individual researchers using regressions with individual fixed effects (see Regressions with individual fixed effects in the Methods), showing an impact penalty that is both substantial and less steep than in the raw data. Within a given researcher's portfolio, the lowest-pivot work was 2.1% more likely ($P < 0.001$ in regression t-test) to have high impact than that researcher's other work, and their highest-pivot work was 1.8% less likely ($P < 0.001$) to have high impact, again showing large deviations from the 5% baseline.

We next considered 1.72 million patents granted from 1980 to 2015 across 127 technology classes, and we similarly calculated the patent-level hit rate based on being in the upper 5% of citations received in the patent's technology classification and application year. We again found a monotonic decrease in impact as pivot size increased (Fig. 2c). The lowest-pivot patents had high impact 8.0% of the time, which is 60% higher than the baseline rate ($P < 0.001$ in one-sample t-test), but the highest-pivot patents had high impact only 3.8% of the time, a 24% reduction from the baseline ($P < 0.001$). This decline in impact with larger pivots was robust to measuring inventor pivots at any technology-classification level, from the broadest to the narrowest (Supplementary Fig. 1). Figure 2d further normalizes impact for individual inventors and continues to show the pivot penalty.

The relationship between pivot size and impact in science has become increasingly negative over the past five decades, both in the raw data (Fig. 2e) and when looking at individual researchers (Extended Data Fig. 1a,b). Furthermore, these findings generalize widely across scientific fields. Studying each of the 154 subfields separately, the negative relationship between impact and pivot size held for 93% of fields, and the increasing severity of the pivot penalty over time occurred in 88% of all scientific fields (Supplementary Table 1). Turning to patenting, we again observed an increasingly steep pivot penalty with time (Fig. 2f). Studying 127 level-2 technology classes separately, the negative relationship between impact and pivot size held in 91% of classes, with the severity of the pivot penalty growing over time in 76% of patent classes (Supplementary Table 2). This steepening pivot penalty among inventors was also seen when using broader or narrower technological classifications (Supplementary Fig. 2). Earlier years for patenting showed flatter, less-monotonic relationships in the raw data (Fig. 2f) and within inventors' portfolios (Extended Data Fig. 1c,d).

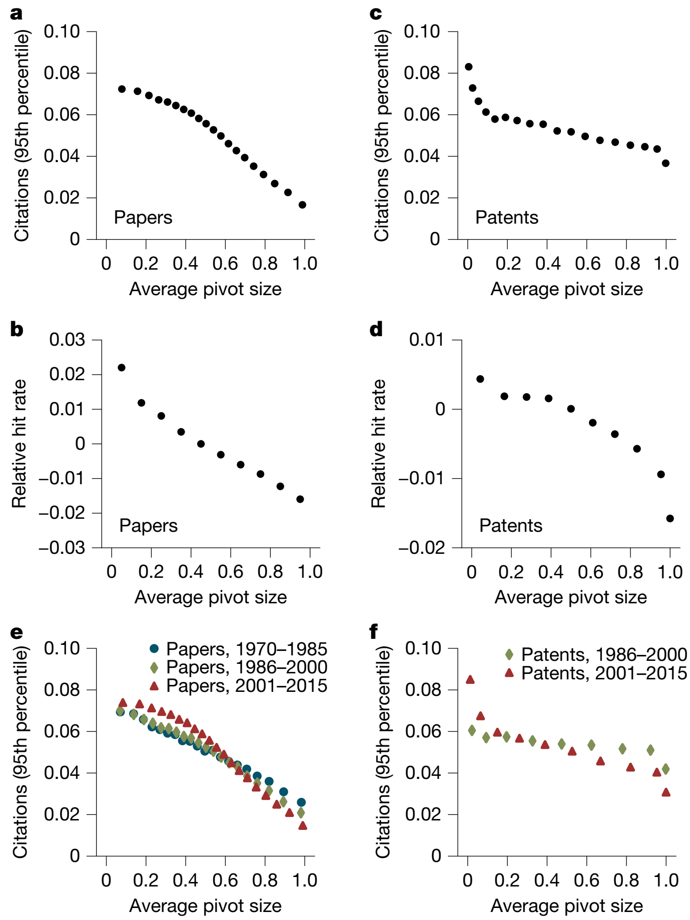

Fig. 2 | The pivot penalty. a, In a study of 25.8 million papers published from 1970 to 2015, papers with higher pivot size have substantially lower probabilities of being high impact. **b**, For a particular author, relative impact for their papers declines steeply with pivot size. **c**, In a study of 1.72 million US patents granted from 1980 to 2015, patents with higher pivot size have substantially lower probabilities of being high impact. **d**, For a particular inventor, relative impact for their patents declines with pivot size. **e**,**f**, Over time, the relationship between pivot size and high-impact works has become increasingly negative in science publishing (**e**) and patenting (**f**).

The findings of a substantial impact penalty are robust to many alternative measures and sample restrictions (see Supplementary sections 2.2–2.3 and 3.1–3.2 for analysis and further examination of high-pivot cases and outlier fields). Robustness tests considered: alternative time windows to determine citation impact (Extended Data Fig. 2); alternative measures of citation impact (Extended Data Fig. 3); sample restrictions to papers with larger reference counts (Supplementary Table 3); alternative pivot-size computation based on referenced papers' field coding, as opposed to their journals (Supplementary Fig. 3); alternative field encodings for patents (Extended Data Fig. 4 and Supplementary Figs. 1, 2 and 4); and hand checks on high-pivot researchers (Supplementary section 3.1).

When examining outcomes, one can also look beyond the citation impact. For papers, we further measured whether a published paper was referenced in a future patent[3,43], indicating the use of the idea beyond science. There was a large decline in patent references to high-pivot articles, with the probability of being cited in a patented invention declining by 43% ($P < 0.001$ in a two-sample t-test) when comparing the highest-pivot with the lowest-pivot vigintiles of papers (Extended Data Fig. 5b). We also examined the propensity for preprints to be published and found that higher-pivot preprints were published at substantially lower rates, with publication rates for the highest-pivot papers declining by 35% ($P < 0.001$) compared with the lowest-pivot papers, indicating another form of the pivot penalty (Extended Data Fig. 6). For patents, we considered the invention's market value based on how a company's stock price moved in response to the patent being issued[44]. The market value of a patented invention decreased steeply with pivot size, declining by 29% ($P < 0.001$) when comparing the highest-pivot with the lowest-pivot patents (Extended Data Fig. 7). These findings indicate that the pivot penalty also appears when considering publication success, practical use and market value, pointing to a constellation of outcomes that go beyond the citation behaviour within a community of researchers.

Altogether, we observed striking empirical regularities that generalize across science and technology. Despite the distinct nature of scientific articles and patents, the institutional contexts in which they are produced, the wide range of research fields and their alternative outcome measures, they have remarkable commonalities: for both scientists and inventors, greater pivots bring large penalties, and this increases over time.

Conceptual frameworks and mechanisms

Our findings indicate that researchers face substantial challenges when entering new subject areas, heightening concerns in innovation communities that research with wide reach or new orientations is difficult[12–14,18,25]. Entering new areas may be challenging as a matter of reception, whereby a scholar has difficulty penetrating new audiences, and it may be challenging as a matter of idea generation, as scholars can face problems generating valuable ideas outside their key areas of competency. To further inform the nature of the pivot penalty, we next examined the pivot penalty in view of both reputational perspectives and idea generation.

An established reputation in a local research community may provide impact advantages within that community but be a relative disadvantage outside it[39]. For example, the 'Matthew effect'[39,40] suggests advantages of established eminence within a community, but 'typecasting'[32,41,45] may undermine the reception when entering new areas. These and other reputational considerations indicate that the pivot penalty may emerge because researchers move beyond their usual audience. To test these considerations, we first examined pivots holding the researcher's field or local audience fixed. Specifically, we examined what happens when a given researcher publishes multiple papers with different pivot sizes but in the same time frame and field, even in the same journal (Supplementary Table 4). We found that the pivot-penalty regression coefficient was approximately 26% less steep (Supplementary Table 4) when an individual published in the same journal, an attenuation that is consistent with a weakening of reputational forces when looking within a common audience, but most of the relationship remained. The pivot penalty thus persisted when the researcher published in a consistent field or before a consistent, local readership. A related approach considered impact within a given, distant audience. Recalling the findings for patented applications (Extended Data Fig. 5) and market value (Extended Data Fig. 7), the pivot penalty also appeared when examining how inventors draw on science or how investors value inventions. These evaluations are made by individuals who are far away from the focal researcher. In sum, the pivot penalty appears not simply as a matter of movement across fields, or from a local audience to a distant audience. Rather, it appears for a researcher within a given field or journal, and it appears within distant communities focused on practical use and market returns.

Reputational considerations may be further informed by considering career stage. Specifically, younger researchers, with less-formed reputations, may see less advantage (the Matthew effect) from staying in a given area or less penalty (typecasting) from venturing outside it[41,46]. Studying career stage, the pivot penalty was slightly stronger (1.6% steeper per year, $P < 0.001$, regression coefficient t-test; Supplementary

Table 5) with advancing career age, consistent with these reputational frameworks. Yet the pivot penalty appears regardless of career stage, including very early in the career (Supplementary Table 5). The findings continued to indicate adaptive challenges, beyond the force of established reputations, when entering new research terrain.

Turning to frameworks of idea generation, a canonical perspective emphasizes an ‘explore versus exploit’ trade-off in creative search. Here, exploitation involves lower-risk but potentially lower-return search around the edges of one’s current focus, whereas exploration involves higher-risk but potentially higher-return forays into more-distant areas[6,37,38]. Related views indicate an advantage of outsiders in bringing new perspectives and driving breakthroughs[10,11,47]. Our analyses looked at upper-tail outcomes, but it is possible that the value of large pivots lies in even rarer, more extreme, positive outcomes. Surprisingly, however, we found that high-pivot research is increasingly under-represented at higher impact levels, whereas low-pivot research has advantages (Supplementary Fig. 5a,b). For example, studying the upper 1% and 0.1% of scientific works by citation impact, papers in the lowest decile of pivot size were over-represented by 65% and 91%, respectively ($P < 0.001$ in one-sample t-tests). By contrast, papers in the highest pivot size decile were under-represented by 69% and 73%, respectively ($P < 0.001$), among the upper 1% and 0.1% of citation impact. Rather than indicating a trade-off between risk and reward in exploratory search, or outsider advantages, these findings continue to indicate a fundamental difficulty of venturing into new areas.

Alternative idea-generation frameworks emphasize the value of specialized expertise. These frameworks link creative advantages less to outsider ideas and more to the accumulated facts, theories and methods built in an area by previous scholars[47,48]. The emphasis on expertise and the value of prior knowledge is consistent with Newton’s famous statement that “if I have seen further, it is by standing on the shoulders of giants”[49]. Furthermore, the steepening of the pivot penalty with time is consistent with increasingly narrow expertise as science progresses and knowledge deepens[12,50,51]. The publication findings (Extended Data Fig. 6) showing a monotonic decline in publication success rates as pivot size increased, and where the highest-pivot preprints were 35% less likely to be published in any journal, suggest the presence of substantive issues with these works, consistent with challenges in moving beyond one’s established areas of expertise. Related creativity frameworks emphasize that new works can be seen as new combinations of existing material[52–54]. Previous studies have shown that high-impact research is characterized primarily by highly conventional mixtures of prior knowledge but also tending to inject, simultaneously, a small dose of atypical combinations that are unusual in previous research[8,55]. Following this literature, we further measured the novelty and conventionality of combinations in a given paper and related these measures to pivot size and impact (Extended Data Fig. 8 and Supplementary Table 9). We found that high-pivot work was associated with a higher propensity for atypical combinations (Extended Data Fig. 8a), a feature also reflected in work linking inventors who switch fields to new technology combinations[14]. For example, 31% of the lowest-pivot vigintile of papers were characterized by high tail novelty, and 49–58% of papers in high-pivot vigintiles had high tail novelty. In other words, when pivoting, a researcher not only does something new personally, but also tends to introduce previously unseen combinations of knowledge to the broader research domain. However, at the same time, high-pivot papers showed distinctly low conventionality (Extended Data Fig. 8b), locating a key characteristic that such exploratory work tends to miss: a prevalence towards well-established mixtures of knowledge. For example, 79% of the lowest-pivot papers exhibited mixtures with high median conventionality, whereas only 27–30% of papers in high-pivot vigintiles had this characteristic. These findings indicate that researchers, as they shift to new areas personally, are equipped for novelty but limited in their relevant or conventional expertise, underscoring the difficulty researchers may face in venturing beyond their specialized knowledge.

Pivoting in response to external events

The pivot penalty indicates that larger pivots are strongly associated with lower impact. However, the research landscape is constantly shifting, and researchers must weigh opportunities nearer to and further from their current research streams. To further probe pivoting behaviour and the pivot penalty, we considered external events that may provoke researchers to pivot. External events can provide quasi-experimental settings and help to establish causal interpretations of the pivot penalty, and may further inform the tensions regarding how researchers navigate a shifting research landscape.

We first considered events that may push researchers away from an existing research stream. Specifically, previous research is sometimes revealed as incorrect or unreliable, which may encourage researchers who had been building on that work to move in new directions. Here we focus on paper retractions, which are of growing interest to the science community[56–58]. Using Retraction Watch and the Dimensions database, we identified 13,455 retractions over the 1975–2020 period. As a treatment group, we considered researchers whose work referenced a retracted paper before it was retracted (but who were not authors of the retracted study). As a control group, we considered researchers who referenced other papers appearing in the same journal and year as the retracted paper. We further used coarsened exact matching[59] to match treated and control authors by their publication rates before the retraction year. We then compared pivots and hit rates between the treatment and control groups, over the four years before and the four years after retraction events, in a difference-in-differences design (Fig. 3a and Difference-in-differences).

We found that pivot sizes increased markedly after a retraction event (Fig. 3b). Consider first the 164,988 treated researchers who referenced a retracted paper at least once before its retraction. The mean pivot size for these researchers’ works after the retraction increased by 2.5% ($P < 0.001$) compared with control researchers’ works. We also studied a smaller treatment group of 18,505 researchers who referenced a retracted paper multiple times, indicating more intensive use. For this group, pivoting was larger, with mean pivot sizes increasing by 3.7% ($P < 0.001$) after the retraction, compared with the control authors (Fig. 3b). Turning to paper impact, treated authors experienced a 0.4% decline ($P < 0.001$) in hit rate after the shock, compared with control authors (Fig. 3c). Among treated authors who drew on the retracted study multiple times, we saw not only larger pivots (Fig. 3b), but also a larger 0.7% decline ($P < 0.001$) in hit rates after the retraction event (Fig. 3c).

Difference-in-differences analyses on a year-by-year basis reinforced these findings. Figure 3d shows an increase in pivoting starting in the retraction year. Similarly, Fig. 3e shows a sustained decline in hit rates after the retraction. Two-stage least-squares regressions, with the retraction event as an instrument, further show that these ‘push’ pivots predict substantial declines in impact (Supplementary Table 6). Robustness tests using hit rates and citation counts over alternative periods, or using alternative definitions of the treated group, showed confirmatory results (Supplementary section 2.7.1, Supplementary Table 6 and Supplementary Figs. 6 and 7). We further considered a smaller case study of replication failures, rather than retractions, drawing on a landmark 2015 study of reproducibility in psychology[60], for which 100 papers were quasi-randomly chosen for evaluation and 64 contained non-reproducible results. Deploying the same treatment and control method as for paper retractions, this smaller study provided confirmatory results for pivoting and impact (Supplementary Section 2.7.2 and Supplementary Table 7). Altogether, we saw pivoting increases and hit-rate declines in response to these external shocks. These analyses further confirm the findings of the pivot penalty, now in response to external events that push authors into new areas.

Beyond push-type events, researchers may also be pulled into new subject areas when new and important research questions emerge.

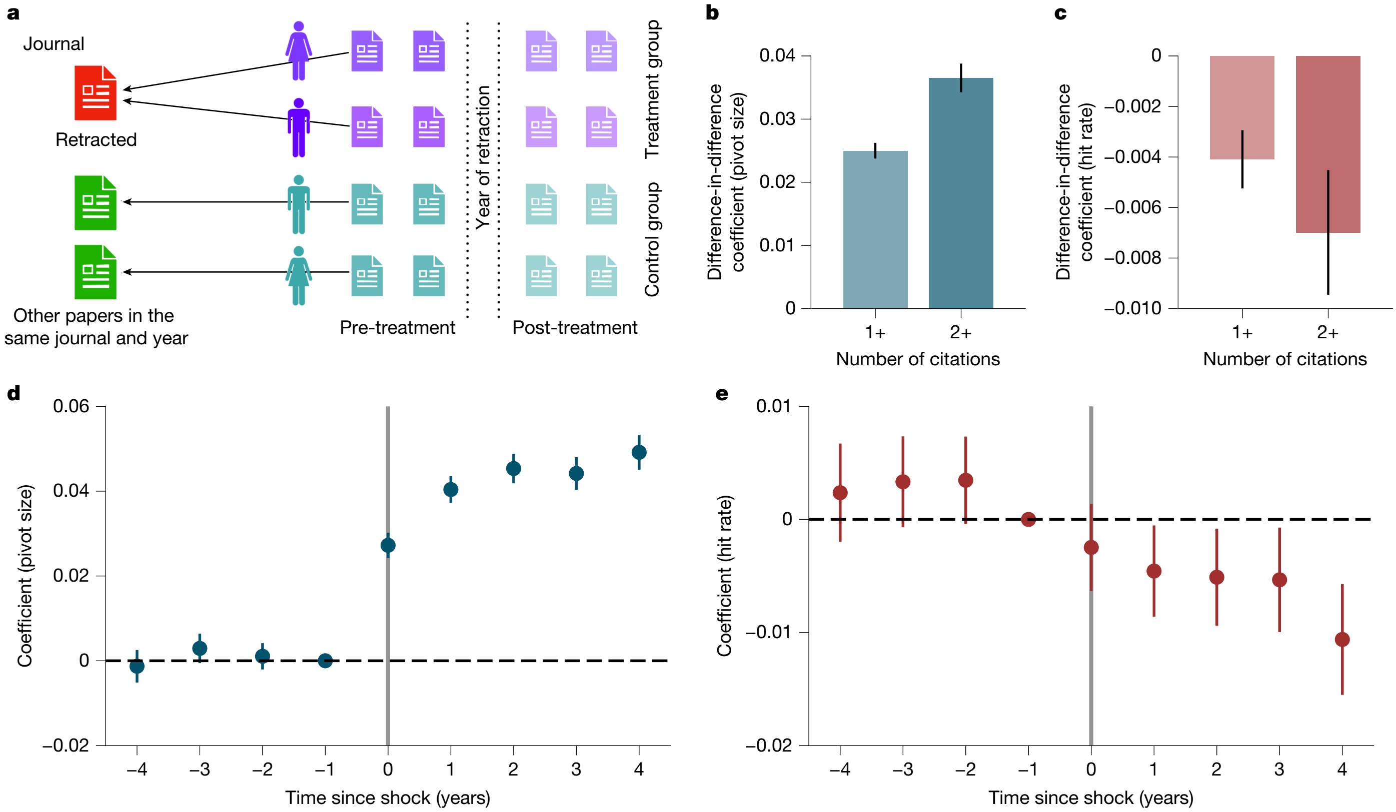

Fig. 3 | Pivots and retraction events. **a**, This difference-in-differences analysis compares treated scientists who directly cite a paper before its retraction with control scientists who cited other papers in the same journal and year as the retracted paper, but not the retracted paper. There are 164,988 treated authors who cited a retracted paper at least once (18,505 treated authors who cited it at least twice) before its retraction but are not themselves authors of the retracted papers. Pivot size and impact of papers from these treated scientists is compared with papers from equal numbers of matched control scientists before and after the year of retraction. **b**, Pivot size significantly increases for treated scientists relative to control scientists after the retraction (0.025 ± 0.001 s.e. pivot-size increase, $P < 0.0001$, regression, $n = 5.82$ million author-by-paper observations). The effect is larger when focusing on scientists who cited the retracted paper at least twice (0.037 ± 0.001 s.e. pivot-size increase, $P < 0.0001$, regression, $n = 2.96$ million author-by-paper observations). **c**, Hit rates fall for treated scientists after retraction (-0.004 ± 0.001, $P < 0.0001$, $n = 5.82$ million), and again the effect is stronger for those citing the retracted paper at least twice (-0.007 ± 0.001, $P < 0.0001$, $n = 2.96$ million). **d**,**e**, Year-by-year analysis comparing treated and control authors further shows that the increase in pivot size is statistically significant ($P < 0.001$) starting immediately in the retraction year (**d**) and the decrease in hit rate becomes statistically significant ($P < 0.05$) starting the year after the retraction (**e**). In **b**–**e**, bars and markers represent the difference-in-differences regression coefficients, and the whiskers show the 95% confidence interval derived from the regression standard errors (see Difference-in-differences). Fig. 3a, icons adapted from Apple.

This leads to our second case study, analysing how researchers shifted to engage with the COVID-19 pandemic. The advent of the pandemic enabled large-scale investigation of individual researcher pivots and further showed how science as a whole responds to a new and consequential demands on the research community. Indeed, confronted by COVID-19, the world looked to science to understand, manage and construct solutions, all in a rapid fashion. Given that few researchers were studying coronaviruses or pandemics before 2020, and none were studying COVID-19 specifically, the emergence of COVID-19 called on researchers across the frontiers of knowledge to consider shifting their work to address new, high-demand research questions[61–63].

Figure 4 shows that pivoting to address COVID-19 was widespread. Although the earliest papers on COVID-19 did not appear until January 2020 (refs. 64,65), by May 2020, 4.5% of all new scientific papers were related to COVID-19 (Fig. 4a). Furthermore, although fields differed in the share of their papers that engaged COVID-19, all fields produced at least some COVID-19-related research (Fig. 4b and Extended Data Fig. 9). Health sciences exhibited the greatest COVID-19 orientation, but the social-science fields of economics, education and law also addressed COVID-19 intensely, speaking to the pandemic's socio-economic challenges[66,67]. Furthermore, studying each field that had at least 20 COVID-19 papers, mean pivot sizes were larger for COVID-19 papers than for other papers in that field (Fig. 4d; mean difference positive for 100% of fields, t-test significant at $P < 0.05$ for 97% of fields). Figure 4c also tracks a cohort of scientists across the body of their work, comparing authors who wrote a COVID-19 paper in 2020 with a control set of authors who did not (Supplementary section S2.8). We found that pivot size presented a clear jump for COVID-19-related work, for which COVID-19 authors pivoted to an unusual degree compared with their own publication history ($P < 0.001$ in t-tests of means), their non-COVID 2020 papers ($P < 0.001$) and the control authors ($P < 0.001$). In sum, unusually large individual pivots were a widespread phenomenon as scientists sought to address COVID-19.

We next turned to impact. Given that 2020 papers have had less chance to receive citations[68], we examined journal placement, for which each journal was assigned the historical hit rate of its publications within its field and year (Supplementary section 2.3). Figure 4e considers papers published in 2020, separating them into 82,900 COVID-19 papers and 2.63 million non-COVID papers. We found a premium associated with COVID-19 papers, as reflected by the upward shift in journal placement, consistent with the extreme interest in the pandemic. Yet the negative relationship between pivoting and impact persisted: comparing the highest-pivot and lowest-pivot bins, COVID-19 and non-COVID-19 papers had declines in hit rate of 61% and

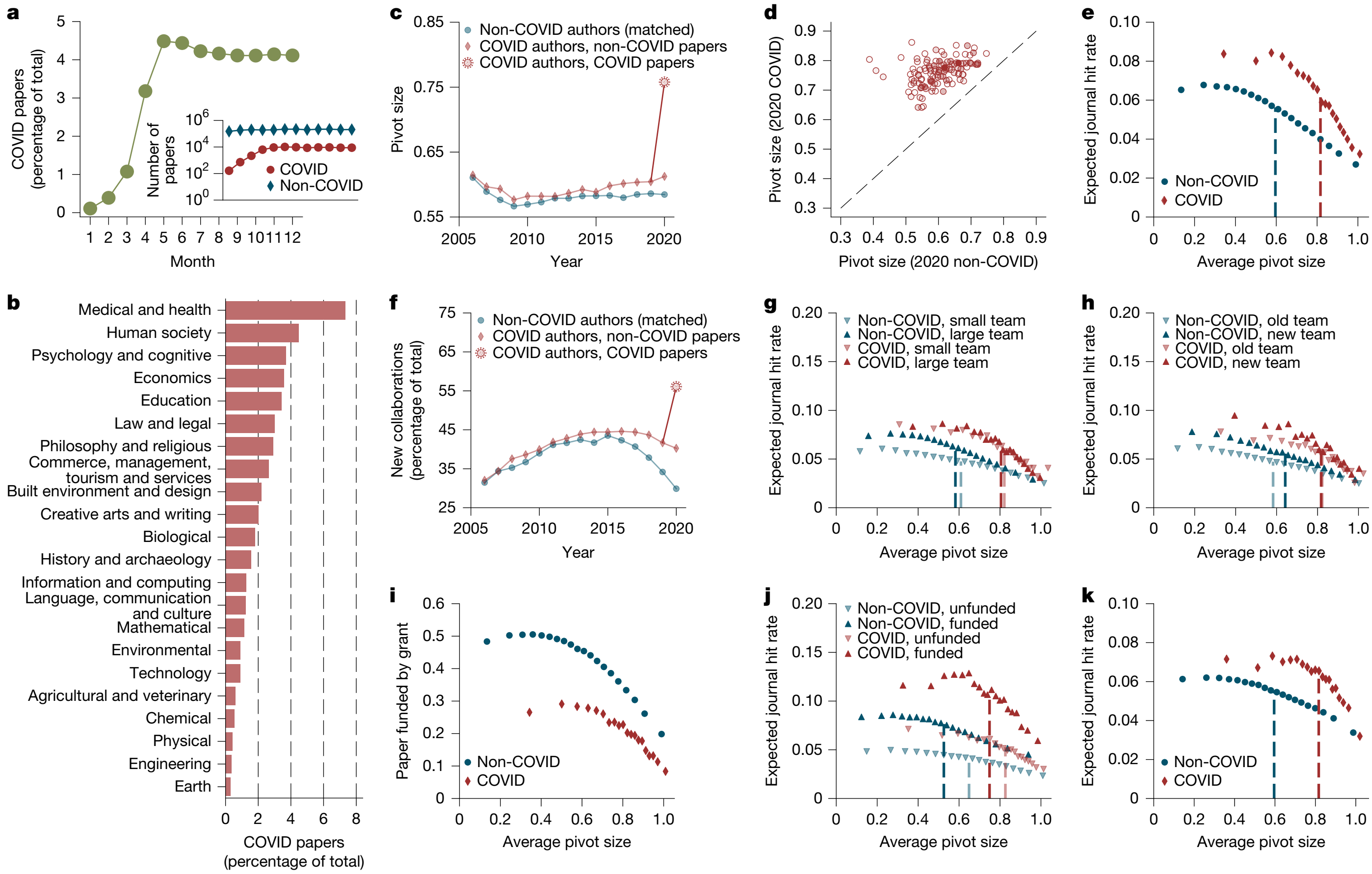

Fig. 4 | Pivots and the COVID-19 pandemic. a, Science rapidly shifted to COVID-19 (COVID) research in 2020, when COVID-19 publications rose to 4.5% of all science publications in May 2020 and maintained high rates thereafter. **b**, Health sciences and social sciences featured the strongest responses, but all scientific fields engaged in COVID-19 research. **c**, Scientists who wrote COVID-19 papers pivoted to a greater extent than they did in their previous work, in their other 2020 work, or than matched control scientists did. **d**, Comparing COVID-19 and non-COVID-19 papers in each field in 2020, unusually large pivots have been a universal feature of COVID-19 research. **e**, COVID-19 papers experienced an impact premium, but the pivot penalty appeared in both COVID-19 and non-COVID-19 work. Comparing at the median pivot sizes (dashed lines), the COVID-19 impact premium was substantially offset by the pivot penalty, given its larger median pivot size. **f**,**g**,**h**, Engaging new collaborators was particularly common for COVID-19 researchers, who worked with new collaborators to an unusual degree compared with their own previous work, their other 2020 publications and with control scientists (**f**). Nonetheless, the pivot penalty persisted for big and small teams (**g**) and when engaging new or existing co-authors (**h**). **i**,**j**, Higher-pivot work was substantially less likely to acknowledge funding support in the sciences as a whole (blue) and among COVID-19 papers (red). COVID-19 papers were particularly unlikely to acknowledge grant support (**i**), yet the pivot penalty appeared even among both funded work and non-funded work (**j**). **k**, Although individual, collaborative and funding features sharply conditioned the adaptive response of science, in regression analysis they did not individually or collectively overcome the fundamental pivot penalty. Coronavirus icon adapted from the Noun Project (https://thenounproject.com).

59%, respectively ($P < 0.001$ in t-tests of means). Thus, scientists who ventured further from their previous work to write COVID-19 papers were not immune to the pivot penalty; rather, they produced research with less impact, on average, relative to low-pivot COVID-19 papers. The pivot penalty in COVID-19 papers also appeared net of individual fixed effects (Supplementary Fig. 8). Importantly, the pivot penalty was sufficiently steep that the COVID-19 impact premium was mostly offset by the unusually large pivots associated with COVID-19 research. For example, the upper 45% of COVID-19 papers by pivot size had lower average journal placement than did non-COVID papers with median or smaller pivot size.

In sum, the 'pull' nature of COVID-19 presented two extremely strong yet contrasting relationships regarding impact. On one hand, this work experienced an impact premium, consistent with the value of researching high-demand areas. On the other hand, greater pivot size markedly predicted less-impactful work. These findings underscore a central tension for individual researchers and the adaptability of science in response to external opportunities: working in a high-demand area has value, but pivoting leads to penalties that offset it.

Building on the science of science literature, we further considered numerous potential moderating factors and forms of heterogeneity that may facilitate pivots. These include researcher career stage, productivity, project-level team size, the use of new co-authors, and funding[8,35,42,69] (see Binned scatterplots and Supplementary section 2.9). For example, early-career researchers may have greater creative flexibility[7,26,47], and larger team size or new co-authors may extend reach[33,70]. When examining impact, however, we found that the pivot penalty persisted, regardless of these features (Fig. 4f–j and Supplementary Table 5). We further used regression methods to incorporate detailed controls for all these potential moderating factors together and found that the pivot penalty appears net of all these features (Fig. 4k), highlighting the depth and breadth of the adaptive challenge.

Discussion

Science must regularly adapt to new opportunities and challenges. The findings in this study, however, highlight difficulties in adapting research streams, with implications for individual researchers, research organizations, and science and society as a whole. At an individual level, a researcher must consider whether to continue exploiting a familiar research stream or explore opportunities that lie further away. Research on creativity reveals the value of exploration, novelty and outsider advantages[6–11,33–35,37], indicating a risk-versus-reward trade-off when researchers venture further from their existing expertise. However, other viewpoints emphasize the value of deep expertise, especially in drawing on the frameworks, facts and tools built by previous scholars[12,47]. As Einstein observed: "Knowledge has become vastly more profound in every department of science. But the assimilative power of the human intellect is and remains strictly limited. Hence it was inevitable that the activity of the individual investigator should be confined to a smaller and smaller section"[50]. Consistent with both Einstein's observation and previous studies indicating increasing specialization and disadvantages when inventors switch fields[12,14], we found that researchers face systematic challenges to pivoting their research, and these increase with time. This pivot penalty applies to knowledge production in both science and technology, generalizes across research subfields and extends beyond impact and publication measures to the practical use and market value of ideas, external to the research domain. Our analyses deploy numerous proxies for quality, such as citation impact, home-run rates, publication success, novelty, conventionality and applied value, but the intrinsic quality of a paper or patent is a multidimensional and open concept.

The pivot penalty also appears in response to external events that may push a researcher away from a given area or pull them into a new one. The enormous demand for COVID-19-related research attracted numerous researchers and provided an impact premium, yet the pivot penalty continued to appear strongly among scholars who reached further to engage with COVID-19 research. All told, the pivot penalty applies to a range of outcomes that are of central interest to researchers and research institutions, and it applies in high-stakes contexts for society as a whole.

The pivot penalty, and its steepening with time, raises key questions for research organizations and research policy. For example, businesses and other organizations are often displaced by new entrants[52,71], despite R&D efforts by the incumbents, which often fail to understand or embrace new technological opportunities[6,38,72]. The pivot penalty underscores this challenge and points towards tactics such as 'acquihires', in which a research organization seeks to hire relevant experts, rather than expecting success by pivoting their existing personnel[73,74].

More broadly, the pre-positioning of researchers seems to be a fundamental constraint on adaptability. In Pasteur's words, "chance favours only the prepared mind", and without the pre-positioning of relevant human capital, the COVID-19 pandemic would probably have been even more costly. Portfolio theory suggests diversified investments as a key tool to manage risk[75], but the pivot penalty indicates that adjustments to the research portfolio are governed by substantial inertia[76]. From this perspective, investing explicitly in a diverse set of scientists is crucial from a risk-management standpoint. A diverse portfolio of investments can then have essential roles in advancing human progress in ordinary times[7,77] and in expanding the capacity to confront emerging challenges.

Science and technology present evolving demands from many areas, from artificial intelligence and genetic engineering to climate change, creating complex issues, risks and urgency. This study shows that pivoting research is difficult, with researchers' pivots facing a growing impact penalty. The pivot penalty not only appears generally across scientific fields and patenting domains, but also arises around important events in science, including when previous research areas become devalued, for example after a paper has been retracted, and when high-demand areas emerge, such as the COVID-19 pandemic. Nevertheless, studying adaptability in different settings and timescales, including longer-run research shifts, are key areas for future work. For example, researchers should consider whether to give up in the likely event of a failed pivot or instead further develop their expertise in the new area and stick to the new path. Exploring such sequential dynamics may help us to better understand how to create conditions to enable adaptive success. Finally, pivoting to address emerging challenges is not unique to science and technology, but may underpin the dynamics of success and survival for individuals, companies, regions and governments across human society[5,72,78–81], indicating that the pivot penalty may be a generic property of many social and economic systems, with potential applicability in broader domains.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-025-09048-1.

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Methods

Pivot size

We quantified researcher pivots using a cosine-similarity metric (Fig. 1a). Specifically, in the sciences, for an author i and a focal paper j, we calculated a vector, $\mathbf{R}_i^j$, representing the distribution of journals referenced by j. Similarly, we counted the frequency in which different journals were referenced in i's previous work, defining a vector $\mathbf{R}_i$. An individual's work includes any paper for which the individual is a listed author. The pivot measure, $\Phi_i{}^j$, is then defined as 1 minus the cosine of these two vectors:

$$\Phi_i{}^j = 1 - \frac{\mathbf{R}_i^j \cdot \mathbf{R}_i}{\|\mathbf{R}_i^j\| \|\mathbf{R}_i\|}. \quad (1)$$

The measure $\Phi_i{}^j$ therefore took the value 0 if the focal paper drew on exactly the same distribution of journals as the author's previous work, and took the value 1 if the focal paper drew entirely on new journals for that author. The measure featured in the main text calculates pivoting in the focal paper compared with the past three years of the author's work. We also calculated our measure by using all previous work of a given author, arriving at similar conclusions (Supplementary section 2.2.1 and Extended Data Fig. 10). Finally, we considered the pivot measure based on the fields of the cited references, rather than their journals, and again found confirmatory results for our main analyses using this alternative measure (Supplementary section 2.2.1 and Supplementary Fig. 3).

For patents, given that journal information was not available, we used technological field codes to define the reference vectors. Specifically, we used the distribution of Cooperative Patent Classification technology field codes among a patent's cited references to build the reference vectors and cosine similarity metric in equation (1). These technology codes are hierarchical, providing alternative levels of granularity in defining technology areas. Our main analyses used the detailed level-4 technological classification (comprising 9,987 distinct technology areas). We further examined all possible classification levels in the Supplementary Information, considering pivoting from the broadest level-1 classification level (9 sections) to the most detailed level-5 classification (210,347 subgroups). Intuitively, the pivot distribution for inventors shifted left when using broader technology categories (Extended Data Fig. 4), so that inventors pivoted less from their broadest technology areas (the section or section-class level). Regardless of the technological classification used, the pivot penalty was robust (Supplementary Fig. 1).

Outcome measures

We used citation-based and non-citation-based outcome measures. Our citation-based measures normalized outcomes for each work by its field and year. For papers, the primary citation measure was an indicator for being in the upper fifth percentile among all articles published in the same year and the same field. The field designation was the L1 field of research designation, for which there are 154 fields in the Dimensions database. For patents, we similarly used an indicator for being in the upper fifth percentile of citations received among all patents from the same year and technology area, using the Cooperative Patent Classification class-level designation, for which there are 128 technology areas.

As presented in the Supplementary Information, we considered numerous alternative citation-based measures. These include smoother (non-binary) outcomes, in which a paper's citation count is normalized by the mean citation counts to articles in the same field and publication year. We further considered the outcome as the percentile rank of the paper's citations among all articles published in the same field and year. To examine time frames, we further considered citation counts over two, five and ten-year forward citation windows. Finally, we considered alternative binary indicators to further emphasize the locus of the very highest-income work, defining a 'hit' paper as being alternatively in the upper 10, 5, 1, 0.5 or 0.1% percent of all publications in a given field and year. Supplementary section 2.3.2 provides further details and associated robustness tests for all these alternatives.

Among the non-citation-based measures, we considered numerous other outcomes. These included measures of publication success, for which we considered preprints from 2015 to 2018 and examined whether they were successfully published over an ensuing five-year window. Drawing on the Reliance on Science database[43], we examined whether a paper appeared as a prior art reference in a future patent, providing an indicator for the usefulness of the idea beyond science[3]. We considered journal placement for recent work. For patents, we also used stock-market event study data[44], providing a market-value measure for patents in publicly traded firms. Supplementary section 2.3.3 provides further details and results for all these outcomes.

Binned scatterplots

To reveal potentially nonlinear relationships between pivot size and outcome variables, we use binned scatterplots[82]. In Fig. 2a, papers are ordered by average pivot size along the x axis and binned into 20 evenly sized groups. Each marker is placed at the mean (x,y) value within each group. Binned scatterplots of raw data are further presented in Figs. 2c,e,f and 4e,g–j, and Extended Data Figs. 2, 3, 5–8 and 10b. Student's t-tests are used to test mean differences from baseline rates (one sample t-tests) or when comparing outcomes between high and low pivot-size vigintiles (two sample t-tests) in raw data. For simplicity, we report $P < 0.001$, but note that with observation counts in the millions, these mean tests tend to reject common means with extremely high t-statistics and extremely low P values.

Figure 4e uses the binned-scatterplot approach for papers in the year 2020, splitting them into articles related or unrelated to COVID-19. Similarly, Fig. 4g–j presents binned scatterplots, further splitting the 2020 papers according to the noted criteria (team size, use of new collaborators and funding). In Fig. 4k, we account for multivariate controls. We consider regression of the form

$$\text{Impact}_i = \alpha + f(\text{Pivot\_size}_i) + \boldsymbol{\theta}\mathbf{X}_i + \varepsilon_i,$$

where $\mathbf{X}_i$ is a vector of control variables with associated vector of coefficients Θ; $f(\text{Pivot\_size}_i)$ allows for a nonlinear relationship between the outcome and pivot size; and ε_i is the error term. Control variables include fixed effects for average previous impact, author age, team size, number of new collaborators and an indicator variable for funding. In practice, we ran two regressions to residualize pivot size and impact, net of the controls, following the Frisch–Waugh–Lovell theorem. Figure 4k presents the binned scatterplot for the residualized measures.

Regressions with individual fixed effects

The panel regression with individual fixed effects in general takes the form:

$$\text{Impact}_{ipt} = \mu_i + \gamma_t + f(\text{Pivot\_size}_{ipt}) + \boldsymbol{\theta}\mathbf{X}_{ipt} + \varepsilon_{ipt},$$

where i indicates a given researcher, p indicates a given work (paper or patent) and t indexes the year (publication year for a paper and application year for a patent); μ_i are individual-fixed effects, γ_t are time-fixed effects and $\mathbf{X}_{ipt}$ is a vector of other potential control variables. Observations are at the paper-by-researcher level. As before, we allowed for potentially nonlinear relationships between pivot size and impact, and hence took a non-parametric approach. Specifically for Extended Data Fig. 1, we generated bins of pivot size and included indicator dummies for a work appearing in the relevant bin. Given the very large number of individual fixed effects, we ran these models in Stata using the reghdfe command suite[83]. Standard errors are clustered at the researcher level. The statistical significance of different pivot-size bin coefficients was calculated using t-tests. For simplicity, we report $P < 0.001$, but note that with observation counts in the millions, these tests present extremely high t-statistics and extremely low P values.

Difference-in-differences

When studying external shocks, we continued to use the researcher panel data model with individual-fixed effects. We implemented standard difference-in-differences methods, comparing treated researchers with control researchers, before and after the external event. The regressions take the form:

$$\text{Pivot\_size}_{\text{ipt}} = \mu_{\text{i}} + \gamma_{\text{t}} + \beta \text{Treat\_Post}_{\text{ipt}} + \gamma \text{Post}_{\text{ipt}} + \varepsilon_{\text{ipt}}$$

$$\text{Impact}_{\text{ipt}} = \mu_{\text{i}} + \gamma_{\text{t}} + \beta \text{Treat\_Post}_{\text{ipt}} + \gamma \text{Post}_{\text{ipt}} + \varepsilon_{\text{ipt}},$$

where Post_{ipt} is an indicator for the period after the shock. The indicator for being in the treatment group is absorbed with an individual's fixed effect and so does not appear separately in the regression. $\text{Treat\_Post}_{\text{ipt}}$ is an indicator for being in the treatment group after the shock and provides the reported difference-in-differences estimate in Fig. 3. The implications of the external event for pivot size and the reduced form results for impact are shown in Fig. 3b,c. We also present 'event study'-style difference-in-differences plots in Fig. 3d,e, showing how the treatment effect evolved before and after the retraction date. Here we replace the $\text{Treat\_Post}_{\text{ipt}}$ variable and Post_{ipt} variable with a series of relative year indicators and their interactions with treatment status.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The de-identified data necessary to reproduce the main plots and statistical analyses (including individual-level pivot size and other key variables) are freely available. Patent data are publicly available at https://patentsview.org/download/data-download-tables. Paper-retractions data are publicly available at https://www.crossref.org/categories/retractions/. NSF grant data are publicly available at https://www.nsf.gov/awardsearch/. NIH grant data are publicly available at https://reporter.nih.gov/. Reliance on Science data are publicly available at https://doi.org/10.5281/zenodo.5803985 (ref. 84). KPSS patent-value data are publicly available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data. Those interested in raw Dimensions data should contact Digital Science directly. Data are available through the main project folder at https://doi.org/10.6084/m9.figshare.28074941 (ref. 85). All other data are available from the corresponding authors upon reasonable request. Source data are provided with this paper.

Code availability

The code necessary to reproduce the main plots and statistical analyses is available at https://doi.org/10.6084/m9.figshare.28074941 (ref. 85).

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Additional information

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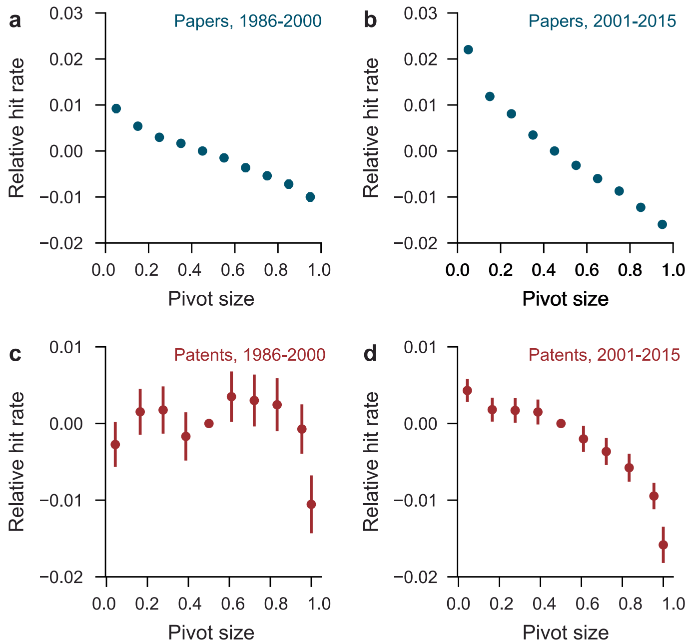
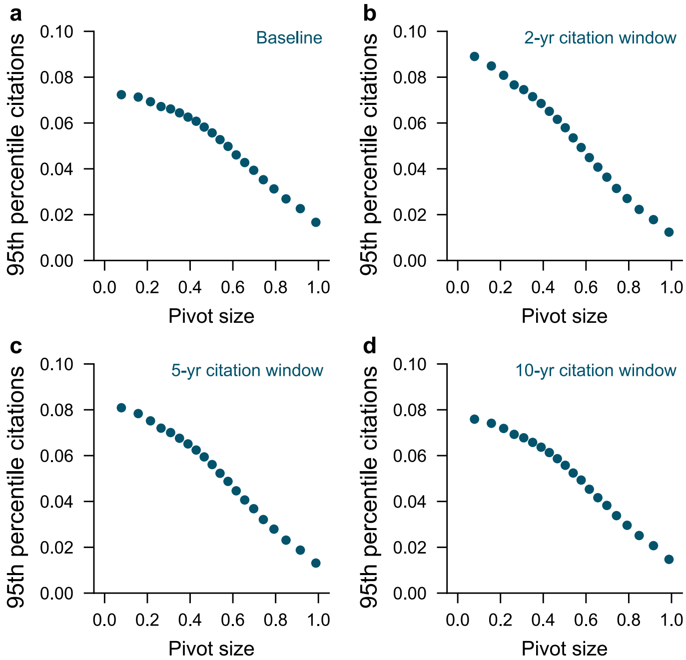
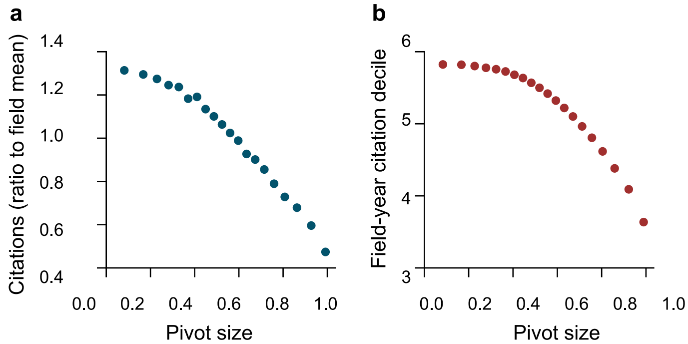
Peer review information *Nature* thanks Erin Leahey and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Peer reviewer reports are available.



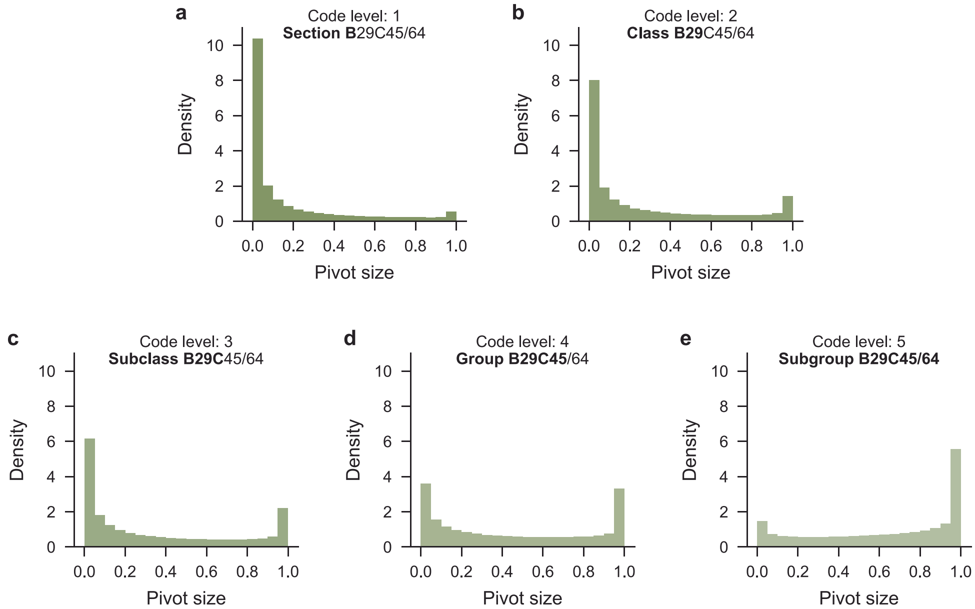
Extended Data Fig. 1 | The pivot penalty in science and invention over time, within individual researchers. Using a 5% subsample of paper authors and all patent inventors, we divide the data into two periods, 1986–2000 (n = 5.7 million author-paper pairs, n = 568 thousand inventor-patent pairs) and 2001–2015 (n = 23.2 million author-paper pairs, n = 2.0 million inventor-patent pairs). In each period, we run regressions with individual fixed effects. (**a**-**d**) The relationship between hit rates and pivot size is estimated non-parametrically, with fixed effects for different ranges of pivot size. The figures present the coefficient for each pivot size group, with indicated 95% confidence intervals. The slope of the pivot penalty is increasing over time when looking within individual researchers. For papers, the recent period (**b**) shows a monotonic decrease in hit rate with pivot size, within the body of work of individual researchers (confidence intervals are too small to be seen). The earlier period (a) similarly shows a monotonic decrease in hit rate with pivot size, but the slope of the relationship is shallower. For patents, the recent period (**d**) shows a monotonic decrease in hit rate with pivot size, within the body of work of individual researchers. The earlier period (**c**) has noisier estimates, with a flatter relationship to pivot size and potential non-monotonicity, but where high pivots face large impact penalties. Overall, we see an increasingly steep pivot penalty with time.



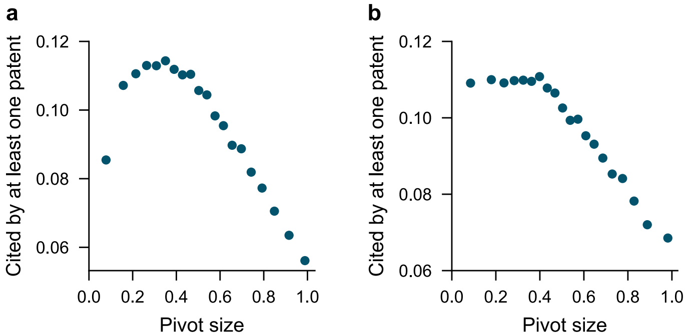
Extended Data Fig. 2 | The pivot penalty over alternative time horizons. The baseline pivot penalty (Fig. 2a) uses the hit rate measure, normalizing impact by field and publication year, providing one means for addressing different time horizons for citations from different publication years. Alternatively, for the same data (n = 25.8 million papers published from 1970–2015), one can count and normalize citations received over a fixed window of time after the publication year. (**b**-**d**) Hit rates are computed using citations received by each paper over, alternatively, (**b**) 2 year, (**c**) 5 year, and (**d**) 10 year forward windows. The pivot penalty is robust using all of these alternatives.



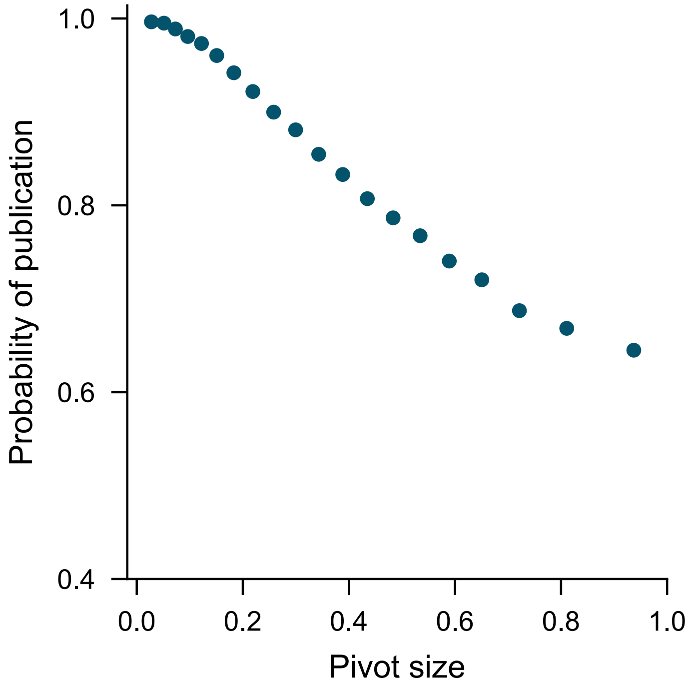
Extended Data Fig. 3 | The pivot penalty with smoother citation measures. In addition to binary measures of impact, one can consider more continuous measures using the same data (n = 25.8 million published from 1970–2015). In (**a**) we normalize each paper's citation count as a ratio to the mean citations for papers in that field and publication year. Citations are approximately 30% above the field mean for low pivot papers on average and 55% below the field mean for the highest pivot papers on average. In (**b**) we normalize each paper's citations by its percentile in the citation distribution for all papers published in the same field and year. The pivot penalty is also robust to this measure of impact.



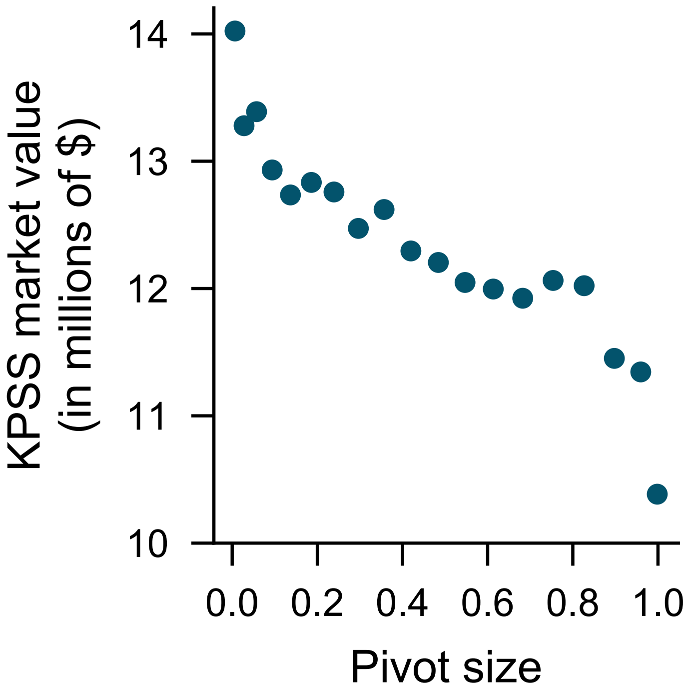
Extended Data Fig. 4 | Quantifying pivot size using various levels of patent technology classification. For patents granted from 1975–2015, the pivot size distribution is bimodal, with more weight on pivots of size zero and one (n = 3.3 million inventor-by-patent observations). The average pivot size increases as the definition of technology class used to calculate pivoting narrows. The available levels of technology class are: (**a**) 9 sections (e.g., "B"), (**b**) 128 classes (e.g., "B29"), (**c**) 662 subclasses (e.g., "B29C"), (**d**) 9,987 groups (e.g., "B29C45"), and (**e**) 210,347 subgroups (e.g., "B29C45/64"). The main analysis in Figs. 1 and 2 use level-4 groups to define pivot size.



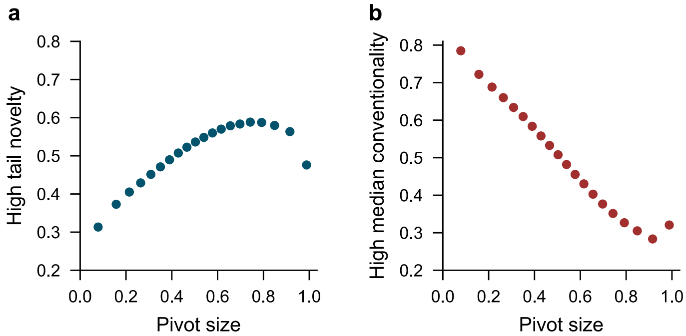
Extended Data Fig. 5 | Patent references to papers. The probability that an academic paper is referenced by at least one patent declines at larger pivot sizes. The data considers 37 million papers published from 1970–2019. Panel (**a**) considers raw data, with no controls, and indicates non-monotonicity at lower pivot sizes. Panel (**b**) considers the relationship net of level-1 field fixed effects, which accounts for the fact that some fields (e.g., astronomy) are far less likely to be referenced in patents than others (e.g., nanotechnology). As seen in the figure, controlling for field largely eliminates the non-monotonicity. Comparing the highest and lowest pivot size bins in (**b**), the probability of being cited in a patented invention declines by 43% ($p < .001$ in two-sample t-test of means).



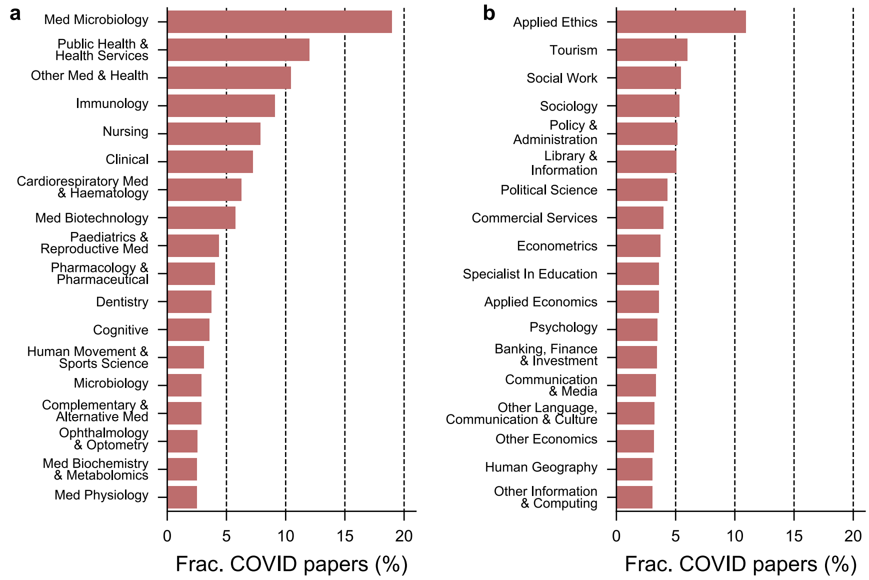
Extended Data Fig. 6 | Successful publication. This figure analyzes all 1.07 million preprints released from 2015–2018 on preprint databases such as arXiv and SSRN. For each preprint, we examine whether it has been published within a five-year window from its preprint date. Virtually all low pivot size papers are published. But publication success declines smoothly with pivot size. Comparing the highest and lower pivot size bins, the publication success rate declines by 35% ($p < .001$ in two-sample t-test of means). The monotonic decline in publication success provides a further dimension of the pivot penalty. See Section S2.3.3 for further discussion.



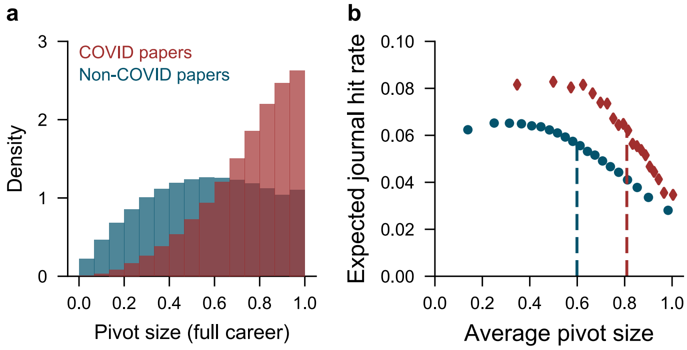
Extended Data Fig. 7 | Patent market value. The estimated market value of patents is decreasing in average pivot size. Market value is estimated using changes in stock prices around the announcement of patent grants for public companies. The sample is 802,599 patents published between 1980 and 2015 that were granted to public corporations. Market valuations are as calculated in[44]. Comparing the highest and lowest pivot size bins, market value declines by 29% ($p < .001$ in two-sample t-test of means).



Extended Data Fig. 8 | Novelty, conventionality and pivot size. The probability that a paper is characterized by (**a**) high tail novelty or (**b**) high median conventionality in relation to pivot size. Measures are calculated using combinations of references in new academic papers, examining 20.8 million papers over the 1970–2015 period[8]. Overall, novelty is increasing with pivot size while conventionality decreases. A researcher who is pivoting not only does something new personally but also tends to combine prior knowledge in a way that is unusual in science. At the same time, high pivots are associated with distinctly low conventionality, consistent with a weaker grounding in conventional domain knowledge.



Extended Data Fig. 9 | COVID share by subfield. This figure reports COVID-19 papers as a fraction of all 2020 publications in specific level-1 fields. Presented here are the 20 medical and 20 non-medical level-1 fields that have the highest fraction of COVID papers.



Extended Data Fig. 10 | Quantifying pivot size using an author's full publication record. In the main text, we measure pivot size comparing the author's focal paper with that author's prior three years of work. Here we examine pivot size using the entire history of that author's work (n = 8.43 million author-paper pairs). (**a**) The large shift in pivot size for COVID papers is evident when pivot size is measured by comparing 2020 papers to all past work. This shift is comparable to Fig. 1b, where pivot size is measured using only papers published in the prior three years. (**b**) The negative relationship between pivot size and impact is similar in slope when using the full career pivot metric here or the 3-year metric as shown in Fig. 4e.

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For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
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☒	☐	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
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☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection.
Data analysis	Data is analyzed with code in Python 3 and Stata 17 using standard software packages within these programs. The code necessary to reproduce main plots and statistical analyses will be freely available at https://doi.org/10.6084/m9.figshare.28074941.v4.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

Deidentified data necessary to reproduce main plots and statistical analyses (including individual-level pivot size and other key variables) are available through the main project folder at https://doi.org/10.6084/m9.figshare.28074941.v4. Patent data is publicly available at https://patentsview.org/download/data-download-tables. Paper retractions data is publicly available at https://www.crossref.org/categories/retractions/. NSF grant data is publicly available at https://www.nsf.gov/

awardsearch/. NIH grant data is publicly available at https://reporter.nih.gov/. Reliance on Science data is publicly available at https://zenodo.org/records/5803985. KPSS patent value data is publicly available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data. Those interested in raw Dimensions data should contact Digital Science directly.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	N/A
Reporting on race, ethnicity, or other socially relevant groupings	N/A
Population characteristics	N/A
Recruitment	N/A
Ethics oversight	N/A

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☒ Behavioural & social sciences ☐ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	This study uses quantitative approaches to study pivot behaviors in science and technology. We assemble and analyze publications data (all publications added to the Dimensions database before December 31, 2020) and patent data (all patents issues by the USPTO from 1976 to the end of 2020).
Research sample	Individual careers as a sequence of scientific publications or technological patents.
Sampling strategy	No statistical methods were used to predetermine sample size. Rather, we analyzed the population of all available records in our datasets.
Data collection	Data collection is based on existing data sources (Dimensions, PatentsView, NSF/NIH grant data, CrossRef, Reliance on Science, and KPSS patent value).
Timing	Raw datasets were downloaded in March 2021, with the exception of the retractions data, which was downloaded in 2024.
Data exclusions	The analysis has no data exclusions. Selection criteria within a dataset are described in the Supplementary Information.
Non-participation	N/A
Randomization	The study is not a randomized experiment. We controlled for covariates using regression models and a difference-in-difference design.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern
☒	☐ Plants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks	*Report on the source of all seed stocks or other plant material used. If applicable, state the seed stock centre and catalogue number. If plant specimens were collected from the field, describe the collection location, date and sampling procedures.*
Novel plant genotypes	*Describe the methods by which all novel plant genotypes were produced. This includes those generated by transgenic approaches, gene editing, chemical/radiation-based mutagenesis and hybridization. For transgenic lines, describe the transformation method, the number of independent lines analyzed and the generation upon which experiments were performed. For gene-edited lines, describe the editor used, the endogenous sequence targeted for editing, the targeting guide RNA sequence (if applicable) and how the editor was applied.*
Authentication	*Describe any authentication procedures for each seed stock used or novel genotype generated. Describe any experiments used to assess the effect of a mutation and, where applicable, how potential secondary effects (e.g. second site T-DNA insertions, mosiacism, off-target gene editing) were examined.*