Adaptability and the Pivot Penalty in Science and Technology

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Scientists and inventors set the direction of their work amidst evolving questions, opportunities, and challenges, yet the extent to which research directions are adaptable remains unclear [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", where the impact of new research steeply declines the further a researcher moves from their prior 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 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 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.

Introduction

Science has been described as an endless frontier [1, 3, 15, 16]. New opportunities and challenges continuously emerge, from synthetic biology to climate change to the COVID-19 pandemic, and both researchers and research organizations must consider adapting their research portfolios to address emergent demands [4, 5, 17-19]. Adaptability is thus critical to 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 themselves, who must regularly consider the direction of their work and their potential to engage new areas. Yet while researchers face consequential choices across large or small changes in their research directions, the degree to which research directions are adaptable depends on fundamental tradeoffs and unknowns. On the one hand, shifts in research may be difficult [14]. 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 reaching further from one's usual research area might be especially 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 while missing opportunities afforded in other areas [6, 38]. Exploring new areas might then be risky but also more likely to produce high impact insights.

Here we study the adaptability of scientists and inventors, examining 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 1970-2020 and U.S. patents granted from 1985-2020 (see SM 1.1-2). The core finding is a substantial "pivot penalty," meaning that the further a researcher moves from their prior work, the worse the research performs in terms of citation impact, publication success, and a host of other outcomes. The negative effects of pivoting appear within individual researchers, across wide-ranging fields of inquiry, and have been steepening over time. We then evaluate the pivot penalty in light 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 where exogenous events can elicit research pivots. We study "push" events, where existing knowledge is revealed to be incorrect or unreliable, pushing researchers away from prior research streams. We then study a "pull" event – the COVID-19 pandemic – that drew researchers into 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 that the pivot penalty persists in each case. The pandemic further allows us to examine a consequential, society-scale event and the capacity of science as a whole to address novel research demands. The paper concludes with discussion of implications of these findings for researchers, research organizations, and science policy.

Measurement Framework

To quantify pivots for researchers, we calculate a cosine-similarity metric that measures the extent to which a given new work departs from a researcher's prior body of work (Fig. 1 and Methods). For papers, we consider the referenced journals, comparing the focal work with the prior 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 the exact same distribution of journals as the author's prior work and takes the value 1 ("full pivot") if the focal paper draws on an entirely novel set of journals. In the patent context, where journal information is not available, we use technological field codes to measure pivots. See Methods and SI for details and alternative constructions of the pivot measure.

Fig. 1 shows the distribution of pivoting behavior, focusing on the year 2020. Overall, we see wide dispersion of pivoting in both the science and patenting contexts, suggesting that pivoting is prevalent for both scientists and inventors, and the size of pivots has high variance (Fig. 1B-C). We also observe a sharp increase in pivot size for COVID-19 related research, where scientists who engaged COVID-19 exhibit unusually large pivots. Whereas non-COVID papers in 2020 present a median of $\overline{\Phi} = 0.60$, COVID-19 papers present a substantially larger median pivot size of $\overline{\Phi} = 0.82$ (p<.0001). The highly variable nature of pivot size is especially prominent in patenting, where we observe a bimodal distribution (Fig. 1C), showing a tendency for both small and large jumps. SI S2.2 provides additional analysis of these patterns, demonstrates their robustness across alternative pivot measures, and offers specific examples of pivoting.

The Pivot Penalty

As scientists and inventors shift from their earlier research, a central question is how impactful their work becomes. We first consider 26 million papers published from 1970 to 2015 across 154 fields. To quantify impact, we calculate a binary, paper-level indicator for whether a given work was in the upper 5% of citations received within its field and publication year [42]. Fig. 2A reveals a striking fact: looking at all of science, works with larger average pivots exhibit systematically lower propensity for high impact. Indeed, we observe a large, monotonic decrease in the average hit rate as the pivot size rises. The lowest-pivot work is high impact 7.4 percent of the time, 48% higher than the baseline rate, whereas the highest-pivot work is high impact only 2.2 percent of the time, a 56% reduction from the baseline. Fig. 2B normalizes impact within individual researchers using regressions with individual fixed effects (see Methods), showing an impact penalty that is both substantial and somewhat less steep than in the raw data. Within a given researcher's portfolio, the lowest-pivot work is 2.1 percentage points (p<.001) more likely to be high impact than that researcher's other work, while their highest-pivot work is 1.8 percentage points less likely (p<.001) to be high impact, again showing large deviations from the 5 percent baseline. A range of robustness tests, including those measuring citation impact in a continuous manner or over different time horizons, produces similar findings (see SI S2.2).

We next consider 1.8 million patents granted from 1980-2015 across 127 technology classes and similarly calculate the patent-level hit rate based on being in the upper 5% of citations received within the patent's technology classification and application year. We find again a monotonic decrease in impact as pivot size increases (Fig. 2C). The lowest pivot patents are high impact 8.0 percent of the time, 60% higher than the baseline rate, while the highest-pivot patents are high impact only 3.8 percent of the time, a 24% reduction from the baseline. This decline in impact with larger pivots is robust to measuring inventor pivots at any technology-classification level, from the broadest to the narrowest (Fig. S4). Fig. 2D further normalizes impact within individual inventors and continues to show the pivot penalty.

Looking across time, 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 within individual researchers (Fig. S5). Furthermore, these findings generalize widely across scientific fields. Studying separately each of the 154 subfields, the negative relationship between impact and pivot size holds for 93% of fields, and the increasing severity of the pivot penalty over time occurs in 88% of all scientific fields (Table S1). Turning to patenting, we again observe an increasingly steep pivot penalty with time (Fig. 2F). Studying separately 127 level-2 technology classes, the negative relationship between impact and pivot size holds in 91% of classes, with the severity of the pivot penalty growing over time in 76% of patent classes (Table S2). This steepening pivot penalty among inventors is also seen when using broader or narrower technological classifications (Fig. S6). Earlier years for patenting show flatter, less monotonic relationships in the raw data (Fig. 2F) and within inventors (Fig. S7).

The findings of a substantial impact penalty are robust to many alternative measures and sample restrictions (see SI section S3 for analysis, as well as further examination of high-pivot cases and outlier fields). Robustness tests include alternative time windows to determine citation impact (Fig S8); alternative citation impact measures (Fig. S9); sample restrictions to papers with larger reference counts (Table S3); redoing pivot size computation based on referenced papers' field coding as opposed to their journals (Fig. S3); and hand checks on high-pivot researchers (Section S3).

In examining outcomes, one can also look beyond citation impact. For papers, we further measure whether a published paper is referenced in a future patent [3, 43], indicating the use of the idea beyond science. We see a large decline in patent references to high-pivot articles, where the probability of being cited in a patented invention declines by 43% comparing the highest-pivot to the lowest-pivot papers (Fig. S10). We also examine the propensity for preprints to become published. We find that higher-pivot preprints publish at substantially lower rates, with publication rates for the highest-pivot papers declining by 35% compared to the lowest-pivot papers, indicating another form of the pivot penalty (Fig. S11). For patents, we consider the invention's market value based on how a company's stock price moves in response to the patent's issuance [44]. The market value of a patented invention decreases steeply with pivot size, declining 29% comparing the highest-pivot to the lowest-pivot patents (Fig. S12). 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 behavior within a community of researchers.

Altogether, we observe striking empirical regularities that generalize across science and technology. Despite the distinct nature of scientific articles and patents, the different institutional contexts in which they are produced, the wide range of research fields, and the alternative outcome measures, these spheres present remarkable commonalities: For both scientists and inventors, greater pivots present large penalties, and increasingly so with time.

Conceptual Frameworks and Potential Mechanisms

The findings suggest substantial difficulties for researchers in entering new areas, and they further heighten concerns in innovation communities that research with wide reach or novel orientations is difficult [12-14, 18, 25]. Entering new areas may be challenging as a matter of reception, where a scholar has difficulty penetrating new audiences, and it may be challenging as a matter of idea generation, where scholars face difficulties generating valuable ideas outside their key areas of competency. To further inform the nature of the pivot penalty, we next examine the pivot penalty in view of both reputational perspectives and idea generation frameworks.

An established reputation in a local research community may provide impact advantages within that community and a relative disadvantage outside it [39]. For example, the "Matthew Effect" [39, 40] suggests advantages of established eminence within a community, while "typecasting" [32, 41, 45] may undermine receptions when entering new areas. These and other reputational considerations suggest that the pivot penalty may emerge because researchers move beyond their usual audience. To test these considerations, we first examine pivots holding the researcher's field or local audience fixed. Specifically, we examine what happens when a given researcher publishes multiple papers with different pivot sizes but in the same time frame and field, and even in the same exact journal (Table S4). We find that the pivot penalty is approximately 28% less steep when an individual is publishing in the same journal, an attenuation consistent with a weakening of reputational forces when looking within a common audience. Yet the large majority of the relationship remains. The pivot penalty thus persists when the researcher publishes in a consistent field or before a consistent, local readership. A related approach considers impact within a given, distant audience. Recalling the findings for market value (Fig. S12) and patented applications (Fig. S10), the pivot penalty also appears 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 tuned to 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, we find some evidence that the pivot penalty appears slightly stronger with advancing career stages, consistent with these reputational frameworks. Yet the pivot penalty remains strong regardless of career stage, including very early in the career (Table S5). The findings continue to suggest adaptive challenges, beyond the force of established reputations, when entering new research terrain.

Turning to idea generation frameworks, a canonical perspective emphasizes an “explore vs. exploit” tradeoff in creative search. Here, exploitation involves lower-risk but potentially lower-return search around the edges of one’s current focus, while exploration involves higher-risk but potentially higher-return departures into more distant areas [6, 37, 38]. Related views suggest an advantage of outsiders in bringing novel perspectives and driving breakthroughs [10, 11, 47]. Our analyses have 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 find that high-pivot research receives lower citations across the entire citation distribution (Fig. S13A). In the very upper tail, such as the upper 1% or 0.1% of citation impact, high-pivot work is even more heavily underrepresented compared to low-pivot work (Fig. S13B). Rather than suggesting a tradeoff between risk and reward in exploratory search, or outsider advantages, these findings continue to suggest a more 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 prior 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]. Further, 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 (Fig. S11), showing that high-pivot preprints are much less likely to be published in any journal, suggest 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]. Prior literature has shown that high-impact research is characterized primarily by highly conventional mixtures of prior knowledge while also tending to inject, simultaneously, a small dose of atypical combinations that are unusual in previous research [8, 55]. Following this literature, we further measure the novelty and conventionality of combinations in a given paper and relate these measures to pivot size and impact (Fig S14, Table S9). We find that high-pivot work is associated with a higher propensity for atypical combinations (Fig. S14A), a feature also reflected in earlier work linking inventors who switch fields to novel technology combinations [14]. In other words, when pivoting, a researcher not only does something new personally but also tends to introduce novel combinations of knowledge to the broader research domain. Yet, at the same time, high-pivot papers show distinctly low conventionality (Fig. S14B), locating a key characteristic that such exploratory work tends to miss: a deep grounding in established mixtures of knowledge. These findings suggest 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. Yet the research landscape itself is constantly shifting, and researchers must weigh opportunities nearer to and further from their current research streams. To further probe pivoting behavior and the pivot penalty, we consider 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 while further informing the tensions in how researchers navigate a shifting research landscape.

We first consider events that may push researchers away from an existing research stream. Specifically, prior 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 locate 13,455 retractions over the 1975-2020 period. As a treatment group, we consider researchers whose work referenced a retracted paper prior to its retraction (but who were not authors of the retracted study). As a control group, we consider researchers who referenced other papers appearing in the same journal and year as the retracted paper. We further use coarsened exact matching [59] to match treated and control authors by their publication rates prior to the retraction year. We then compare pivots and hit rates between the treatment and control groups, over the four years before and four years after retraction events, in a difference-in-differences design. See Fig. 3A and Methods.

We find that pivot sizes increase markedly after a retraction event (Fig. 3B). Consider first the 164,988 treated researchers who referenced a retracted paper at least once prior to its retraction. The mean pivot size for these researchers' works after the retraction increases by 2.5 percentage points ($p<.001$) compared to control researchers' works. We further study a smaller treatment group of 18,505 researchers who referenced a retracted paper multiple times, indicating more intensive use. For this group, pivoting is larger, with mean pivot sizes increasing by 3.7 percentage points ($p<.001$) after the retraction, compared to the control authors (Fig. 3B).

We next examine paper impact. Treated authors experience a 0.4 percentage point decline ($p<.001$) in hit rate after the shock, compared to control authors (Fig. 3B). Among treated authors who drew on the retracted study multiple times, we see not only larger pivots (Fig. 3B, left) but also a larger 0.7 percentage point decline ($p<.001$) in hit rates after the retraction event (Fig. 3B, right).

Difference-in-differences analyses on a year-by-year basis reinforce these findings. Fig. 3C shows a sharp increase in pivoting starting in the retraction year. Similarly, Fig. 3D shows a sustained decline in hit rates starting in the retraction year. Two-stage least squares regressions, with the retraction event as an instrument, further show that these "push" pivots predict substantial declines in impact (Table S6). Numerous robustness tests are considered in the SI using different citation measures and timing (Table S6, Fig. S16). We further consider a smaller case study of replication failures, rather than retractions, drawing on the landmark 2015 study of reproducibility in psychology [60], where 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 provides confirmatory results for pivoting and impact (SI Section 2.6.1, Table S7). Altogether, we see 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" treated authors into new areas.

Beyond push-type events, researchers may also be pulled into new areas when novel and important research questions emerge. This leads to our second case study, analyzing how researchers shifted to engage the COVID-19 pandemic. The advent of the pandemic allows high-scale investigation of individual researcher pivots while further unveiling how science as a whole responds to a new and consequential demand upon the research community. Indeed, confronted by COVID-19, the world looked to science to understand, manage, and construct solutions, all in rapid fashion. Given that few researchers were studying coronaviruses or pandemics prior to 2020—and none were studying COVID-19 specifically—the emergence of COVID-19 called upon 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 [64, 65], by May 4.5% of all new scientific papers were related to COVID-19 (Fig. 4A). Further, while fields differed in their rate of pivoting, all fields pivoted to COVID-19 related research (Fig. 4B). Health sciences exhibit the greatest COVID-19 orientations, while social science fields – including economics, education, and law – also addressed COVID-19 relatively heavily, speaking to the pandemic's socioeconomic challenges [66, 67]. Furthermore, while fields inherently differ in their propensities to produce COVID-19 research (Figs. 4B, S17), we find that scientists in every field undertake unusually large pivots when writing COVID-19 related papers. Fig. 4C further tracks a cohort of scientists across the body of their work. It compares authors who wrote a COVID paper in 2020 and a control set of authors who did not (see Methods). We find that pivot size presents a clear jump for COVID-related work, where COVID authors pivoted to an unusual degree compared to their own prior history, to their non-COVID 2020 papers, and to the control authors. In sum, unusually large individual pivots were a widespread phenomenon as scientists sought to address COVID-19.

We next turn to impact. Given that 2020 papers have had less chance to receive citations [68], we examine journal placement, where each journal is assigned the historical hit rate of its publications within its field and year (see SI S2.2). Fig. 4E considers all papers published in 2020, separating them into COVID and non-COVID papers. We find a large premium associated with COVID-19 papers, as reflected by the substantial upward shift in journal placement, consistent with the extreme interest in the pandemic. Yet the negative relationship between pivoting and impact persists and remains steep. Thus, scientists who traveled further from their prior work to write COVID-19 papers were not immune to the pivot penalty; rather they produced research with substantially less impact on average relative to low-pivot COVID papers. These results also appear net of individual fixed effects (Fig. S18). Importantly, the pivot penalty is sufficiently steep that the COVID impact premium is mostly offset by the unusually large pivots associated with COVID research. For example, the upper 45% of COVID-19 papers by pivot size have lower average journal placement than non-COVID papers with median or smaller pivot size.

In sum, the "pull" nature of COVID-related work presents two extremely strong yet contrasting relationships regarding impact. On the one hand, this work has experienced an impact premium, consistent with the value of researching high-demand areas. On the other hand, greater pivot size markedly predicts less impactful work. These findings underscore a central tension for individual researchers and the adaptability of science in response to external opportunities: while working in a high-demand area has value, pivoting exhibits offsetting penalties.

Building on the science of science literature, we further consider 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 coauthors, and funding (see Methods and SI S2.8) [8, 35, 42, 69]. For example, early career researchers may have greater creative flexibility [7, 26, 47], and larger team size or new coauthors may extend reach [33, 70]. When examining impact, however, we find that the pivot penalty persists regardless of these features (Fig. 4F-J, Table S5). We further use regression methods to incorporate detailed controls for all these features together, finding that, net of all these features, the pivot penalty moderates only slightly and remains substantial in magnitude (Fig. 4K), highlighting the depth and breadth of the adaptive challenge.

Discussion

Science must regularly adapt to new opportunities and challenges. Yet the findings in this paper point to significant 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 weigh whether to continue exploiting a familiar research stream against opportunities that stand further away. Research on creativity suggests the value of exploration, novelty, and outsider advantages [6-11, 33-35, 37], suggesting a risk vs reward tradeoff as researchers venture further from their prior expertise. However, other viewpoints emphasize the value of deep expertise, especially in drawing upon the frameworks, facts, and tools built by prior 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 Einstein's observation, as well as prior studies indicating increasing specialization and disadvantages when inventors switch fields [12, 14], we find that researchers face systematic challenges to pivoting research, and increasingly so 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. While our analyses deploy numerous proxies for quality—such as citation impact, home-run rates, publication success, novelty, conventionality, and applied value—the intrinsic quality of a paper or patent is a multidimensional and open concept.

The pivot penalty further appears in response to external events that may push a researcher away from a given area or pull them into a new one. In the COVID-19 pandemic, the enormous demand for COVID-related research attracted numerous researchers and provided an impact premium; yet the pivot penalty continues to appear strongly among scholars who reached further to engage COVID research. All told, the pivot penalty applies to a range of outcomes that are of central interest to researchers and research institutions and 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 like "acquihires," where the research organization seeks to hire relevant experts rather than expect success by pivoting their existing personnel [73, 74].

More broadly, the pre-positioning of researchers appears to be a fundamental constraint on adaptability. In Louis Pasteur's famous words, "chance favors only the prepared mind," and without the pre-positioning of relevant human capital the coronavirus pandemic would likely have been still more costly. Portfolio theory points to diversified investments as a key tool to manage risk [75], but the pivot penalty suggests that adjustments to the research portfolio are governed by substantial inertia [76]. From this perspective, investing explicitly in a diverse set of scientists becomes critical from a risk management standpoint. A diverse portfolio of investments can then play essential roles in both advancing human progress in ordinary times [7, 77] while also expanding human capacity to confront novel challenges.

Science and technology present evolving demands from many areas – from artificial intelligence to genetic engineering to climate change – creating complex issues, risks, and urgency. This paper shows that pivoting research is difficult, with researchers' pivots facing a growing impact penalty.

It is notable that the pivot penalty not only appears generally across scientific fields and patenting domains, but also appears amidst major events in science, including when prior areas become devalued, as in the retraction context, and when high-demand areas emerge, as in the COVID-19 pandemic. Nevertheless, studying adaptability in different settings and time scales, including longer-run research shifts, are key areas for future work. For example, should a researcher give up in the likely event of a failed pivot or alternatively further develop their expertise in the new area and stick to the new path? Exploring such sequential dynamics may help us better understand how to create conditions to facilitate adaptive success. Lastly, pivoting to address new challenges is not unique to science and technology but may underpin the dynamics of success and survival for individuals, firms, regions, and governments across human society [5, 72, 78-81], suggesting the pivot penalty may be a generic property of many social and economic systems, with potential applicability in broader domains.

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Data availability Deidentified data necessary to reproduce main plots and statistical analyses (including individual-level pivot size and other key variables) will be made freely available. 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/. 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.v1.

Code availability Code necessary to reproduce main plots and statistical analyses are available at https://doi.org/10.6084/m9.figshare.28074941.v1.

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Figure 1. Quantifying Research Pivots. (**a**) The pivot measure compares a focal work against prior works by the same researcher. An increasing value on the [0,1] interval indicates a larger pivot from the researcher's prior work. In the sciences, journals are used to define research areas (pictured); in patenting, technology classes are used. The distributions of pivots in 2020 show wide dispersion in science (**b**) and in patenting (**c**). COVID-19 papers show higher pivots (**b**) than other papers in 2020.

Figure 2. The Pivot Penalty. (a) Studying 26 million papers published from 1970-2015, papers with higher pivot size present substantially lower probabilities of being high impact. (**b**) Further, for a given author, relative impact among their papers declines steeply with pivot size. (**c**) Studying 1.8 million U.S. patents granted from 1980-2015, patents with higher pivot size present substantially lower probabilities of being high impact. (**d**) Further, for a given inventor, relative impact among their patents declines with pivot size. Over time, the relationship between pivot size and high impact works has become increasingly negative in science (**e**) and patenting (**f**).

Figure 3: Pivots and Retraction Events. (**a**) The difference-in-differences analysis compares treated scientists who directly cite a paper prior to its retraction to control scientists who cited other papers in the same journal and year as the retracted paper. Pivot size and impact of treated scientists is compared to control scientists before and after the year of retraction. (**b**) Pivot size significantly increases for treated scientists relative to control scientists after the retraction. The effect is larger when focusing on scientists who cited the retracted paper at least twice. Hit rates fall for treated scientists after retraction, and again the effect is stronger for those citing the retracted paper at least twice. A year-by-year analysis again shows a marked increase in pivot size (**c**) and a decrease in hit rate (**d**) for treated authors relative to control authors, starting in the retraction year. Error bars present 95% confidence intervals.

Figure 4. Pivots and the COVID-19 Pandemic. (**a**) Science rapidly shifted to COVID-19 research in 2020, with COVID-19 publications rising to 4.5% of all science publications in May 2020 and maintaining similarly high rates thereafter. (**b**) While health sciences and social sciences featured the strongest responses, all scientific fields engaged COVID-19 research. (**c**) Comparing COVID and non-COVID papers within each field in 2020, unusually large pivots have been a

universal feature of COVID-19 research in all 154 subfields of science. (**d**) Scientists who write COVID-19 papers pivot to a greater extent than they do in their prior work, their other 2020 work, or matched control scientists' do. (**e**) COVID-19 papers experience an impact premium, but the pivot penalty appears within both COVID and non-COVID work. Comparing at the median pivot sizes (dashed lines), the COVID-19 impact premium is substantially offset by the pivot penalty, given its larger median pivot size. (**f**) Engaging new collaborators was especially common for COVID-19 researchers, who worked with new collaborators to an unusual degree compared to their own prior history, their other 2020 publications, and control scientists. Nonetheless, the pivot penalty persists for big and small teams (**g**) and when engaging new or existing coauthors (**h**). (**i**) Funding support is heavily oriented to lower pivot work. Higher-pivot work is substantially less likely to acknowledge funding support in the sciences as a whole (blue) and among COVID-19 papers (red). COVID-19 papers were especially unlikely to acknowledge grant support. Yet the pivot penalty appears even among both funded and non-funded work (**j**). (**k**) While individual, collaborative, and funding features sharply condition the adaptive response of science, in regression analysis they do not individually or collectively overcome the fundamental pivot penalty.

Methods

Pivot Size

We quantify researcher pivots using a cosine-similarity metric (Fig. 1A). Specifically, in the sciences, for an author *i* and a focal paper *j*, we calculate a vector R_i^j, representing the distribution of journals referenced by *j*. Similarly, we count the frequency in which different journals are referenced in the union of *i*'s prior work, defining a vector R_i. An individual's works include any paper where the individual is a listed author. The pivot measure, Φ_i^j, is then defined as 1 minus the cosine of these two vectors:

$$\Phi_i^j = 1 - \frac{R_i^j \cdot R_i}{\|R_i^j\|\|R_i\|} \tag{1}$$

The measure Φ_i^j thus takes the value 0 if the focal paper draws on exactly the same distribution of journals as the author's prior work and takes the value 1 if the focal paper draws entirely novel journals for that author. The measure featured in the main text calculates pivoting in the focal paper compared to the prior three years of the author's work. We also calculate our measure by using all prior work of a given author, arriving at similar conclusions (see SI S2.2.1 and Fig. S1). Finally, we consider the pivot measure based on the fields of the cited references, rather than their journals, and again find confirmatory results for our main analyses using this alternative measure (see SI S2.2.1 and Fig. S3).

For patents, given that journal information is not available, we use technological field codes to define the reference vectors. Specifically, we use the distribution of Cooperative Patent Classification (CPC) technology field codes among a patent's cited references to build the reference vectors and cosine similarity metric in (1). These technology codes are hierarchical, providing alternative levels of granularity in defining technology areas. Our main analyses use the detailed level-4 technological classification (comprising 9,987 distinct technology areas). We further examine 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 shifts leftward when using broader technology categories (Fig. S2), so that inventors pivot less from their broadest technology areas (the section or section-class level). Regardless of the technological classification used, the pivot penalty appears robustly (Fig. S4).

Outcome Measures

We use citation-based and non-citation-based outcome measures. Our citation-based measures normalize outcomes for each work by its field and year. For papers, the primary citation measure is an indicator for being in the upper 5th percentile among all articles published in the same year and same field. The field designation is the L1 field of research designation, for which there are 154 fields in the Dimensions database. For patents, we similarly use an indicator for being in the upper 5th percentile of citations received among all patents from the same year and technology area, using the CPC class level designation, for which there are 128 technology areas.

As presented in the SI, we consider numerous alternative citation-based measures. These include smoother (non-binary) outcomes, where a paper's citation count is normalized by the mean citation counts to articles in the same field and publication year. We further consider 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 consider citation counts over two, five, and ten-year forward citation windows. Finally, we consider 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. Section S2.2.1 provides further details and associated robustness tests for all these alternatives.

Among non-citation-based measures, we consider numerous additional outcomes. These include measures of publication success, where we consider preprints from 2015-2018 and examine whether they are successfully published over an ensuing five-year window. Drawing on the Reliance on Science database [82], we examine whether a paper appears as a prior art reference in a future patent, providing an indicator for the usefulness of the idea beyond science [83]. We consider journal placement for recent works. For patents, we also use stock market event study data from [84], providing a market value measure for patents in publicly traded firms. Section S2.2.2 provides further details and results for all these outcomes.

Binned Scatterplots

To reveal potentially non-linear relationships between pivot size and outcome variables, we use binned scatterplots [85]. 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. Fig. 2C uses the same approach for patents. Fig. 4E uses the bin scatterplot approach for year 2020 papers, splitting them into COVID and non-COVID related articles. Similarly, Figs. 4F-J present bins 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

$$Impact_i = \alpha + f(Pivot\_size_i) \ + \boldsymbol{\theta X_i} + \varepsilon_i$$

where $\boldsymbol{X_i}$ is a vector of control variables and $f(Pivot\_size_i)$ allows for non-linear relationship between the outcome and pivot size. Control variables include fixed effects for average prior impact, author age, team size, number of new collaborators, and an indicator variable for funding. In practice we run two regressions to residualized pivot size and impact, net of the controls, following the Frisch-Waugh-Lovell theorem. Fig. 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:

$$Impact_{ipt} = \mu_i + \gamma_t + f(Pivot\_Size_{ipt}) + \boldsymbol{\theta X_{ipt}} + \varepsilon_{ipt}$$

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). The μ_i are individual fixed effects, the γ_t are time fixed effects, and $\boldsymbol{X_{ipt}}$ is a vector of other potential control variables. As before, we allow for potentially non-linear relationships between pivot size and impact and hence take a non-parametric approach. Specifically, we generate bins of pivot size and include indicator dummies for a work appearing in the relevant bin. Given the very large number of individual fixed effects, we run these models in Stata using reghdfe command suite [86]. Standard errors are clustered at the researcher level.

Differences-in-Differences

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

$$Pivot\_Size_{ipt} = \mu_i + \gamma_t + \beta Treat\_Post_{ipt} + \gamma Post_{ipt} + \varepsilon_{ipt}$$

$$Impact_{ipt} = \mu_i + \gamma_t + \beta Treat\_Post_{ipt} + \gamma Post_{ipt} + \varepsilon_{ipt}$$

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. $Treat\_Post_{ipt}$ is an indicator for being in the treatment group after the shock and provides the reported difference-in-differences estimate. The implications of the external event for pivot size and the reduced form results for impact are both shown in Fig. 3B. We also show "event study" style differences-in-differences plots in Fig. 3C-D, to show how the treatment effect evolved before and after the retraction date. Here we replace the binary treatment times post variable with a series of relative year indicators, each interacted with treatment status.

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