nature portfolio

https://doi.org/10.1038/s41586-025-09048-1

Supplementary information

The pivot penalty in research

In the format provided by the authors and unedited

Supplementary Information for
The Pivot Penalty in Research

Ryan Hill[1,2¶], Yian Yin[1,3,4,5¶], Carolyn Stein[6,7], Xizhao Wang[2], Dashun Wang[1,2,3,4,8*], Benjamin F. Jones[1,2,3,9*]

[1]Center for Science of Science and Innovation, Northwestern University, Evanston, IL, USA

[2]Kellogg School of Management, Northwestern University, Evanston, IL, USA

[3]Ryan Institute on Complexity, Northwestern University, Evanston, IL, USA

[4]McCormick School of Engineering, Northwestern University, Evanston, IL, USA

[5]Department of Information Science, Cornell University, Ithaca, NY, USA

[6]Haas School of Business, University of California – Berkeley, Berkeley, CA, USA

[7]Department of Economics, University of California – Berkeley, Berkeley, CA, USA

[8]Northwestern Innovation Institute, Northwestern University, Evanston, IL, USA

[9]National Bureau of Economic Research, Cambridge, MA, USA

[¶]These authors contributed equally to this work.

[*]Correspondence to: dashun.wang@northwestern.edu, bjones@kellogg.northwestern.edu.

This supplementary information (SI) file provides further detail and background information for "The Pivot Penalty in Research." This SI considers each data source and each method used. Numerous robustness tests to the main results are also provided.

Table of Contents

S1 Data description

S1.1 Publications data

Our primary dataset for scientific publications is based on Dimensions, a data product from Digital Science[1,2]. Dimensions is one of the world's largest citation databases, including scientific publications from journals, conference proceedings, books and chapters, and preprint servers. For each paper we obtain its title, publishing venue, list of authors, affiliation(s), publication date, fields of study, references, number of citations received, and acknowledged funding information. We collect all publications in the Dimensions database through December 31, 2020, and our analysis covers publications over the 1970-2020 period.

Our baseline dataset is restricted to the 45.2 million papers that include at least five references to prior work. We do this for two reasons. First, pivot size — our primary variable of interest — uses reference information as a proxy of a paper's knowledge sources. Second, this restriction helps filter out non-research articles and incomplete records. A manual check of a random sample of excluded papers (those with 4 or less references to prior work) shows that many are commentary or editorial pieces that cite very few references, while some are due to the lack of reference data sharing between Dimensions and some publishers. As robustness checks, we also consider further analyses where reference counts exceed successively higher thresholds, including at least 15, 20, 30 or 50 references to prior work (see SI Section S2).

Recent studies have shown that Dimensions covers most reference-citation linkages as recorded in other bibliographic databases, such as the Web of Science or Scopus[3]. For publications with preprint linkages, we further combine the published and preprint article into a single record and count citations as the sum of citations to the combined record. For most journal articles (99.2%) and all preprint publications, we have information on its publishing venue (i.e., specific journal or preprint series).

Author name disambiguation An important step in science of science studies is author name disambiguation. Dimensions has developed a systematic algorithm using both internal information derived from papers (e.g., affiliation and citations) as well as external author profile information (e.g., ORCID). Within our sample, 84.6% of records in the data are assigned author IDs. Analyses are restricted to papers with at least one disambiguated author. We further hand check random samples of papers and author IDs against public CVs, which indicates high quality matching of authors and their papers (see SI Section S3).

Affiliation disambiguation Dimensions has also mapped raw affiliation strings to the Global Research Identifier Database (GRID), which provides unique identifiers for different research organizations, offering unique affiliation IDs to 75.1% of records in the data.

Field classification Dimensions also implements classification approaches to assign fields under the FOR (field of research), a two-level field classification system (22 level-0 fields and 154 level-1 fields). Across all of Dimensions, 94.3% and 88.6% of papers have at least one level-0 and level-1 field, respectively. The median number of level-0 (L0) fields per paper is 1 and the median number of level-1 (L1) fields per paper is 1. In analyses where we calculate field-specific means, we associate papers to each of the fields they belong to, when the paper has multiple fields.

Retracted publications For the retraction natural experiment, we start with the complete list of retracted papers produced by the Retraction Watch Database and CrossRef. This retractions data has become open source and available through CrossRef[4]. We merge retracted papers based on DOI to the Dimensions database (through 2020). This merge identifies 13,455 retracted papers in the Dimensions database over the 1975-2020 period. See Methods below for the construction of the treatment and control groups and further details.

Replication failures As a substantially smaller case study, we use the landmark replication analysis in 2015, "Estimating the reproducibility of psychological science" [5]. Specifically, we take all publications in Dimensions that appear in three journals (*Psychological Science*, *Journal of Personality and Social Psychology*, and *Journal of Experimental Psychology: Learning,* *Memory, and Cognition*) in 2008, which were the source of the 100 publications that were quasi-randomly selected and analyzed in the replication study. Of the tested papers, 64 had results that failed to replicate. See Methods below for the construction of the treatment and control groups and further details.

COVID-19 related publications We constructed a set of COVID-19 related publications using a keyword search method and following previous work[6] by searching for papers published in 2020 with the following query:

"2019-nCoV" OR "COVID-19" OR "SARS-CoV-2" OR "HCoV-2019" OR "hcov" OR "NCOVID-19" OR "severe acute respiratory syndrome coronavirus 2" OR "severe acute respiratory syndrome corona virus 2" OR (("coronavirus" OR "corona virus") AND (Wuhan OR China OR novel))

Since our primary interest is papers closely related to the COVID-19 pandemic, we limit the search to the title and abstract, yielding 95.5 thousand COVID-related papers.

S1.2 USPTO patents data

We further leverage USPTO patents to test the pivot penalty in technological areas. Our data comes from bulk data services provided by PatentsView (retrieved in March 2021), a patent data platform supported by USPTO. The original data covers 6.9 million patents granted by USPTO since 1976, with detailed information on the patent's title, date, CPC classification codes, patent references, and (disambiguated) inventors.

For our analysis, we focus on utility patents. Given that we are primarily interested in career-level pivot behaviors, we exclude all patent continuations (by definition, they will be highly similar to previous patents by the same inventor). To this end, we further retrieve the application numbers of all patents in our dataset and link them with continuation information from the Patent Examination Research Dataset (PatEx). We then remove all patents that are associated with at least one "parent" patent in continuation records. Consistent with our selection on publication data (S1.1), we further focus on patents with at least 5 patent references. This results in a subset of 3.7 million patents, and 3.0 million patents of over our main analysis period, 1980-2015.

Inventor name disambiguation PatentsView has also developed an inventor name disambiguation algorithm, which assigns a unique id for each inventor record in the database. More details about the algorithm are available at https://github.com/PatentsView/PatentsView-Disambiguation. We use this information to construct inventor career trajectories. See Methods below.

Technology classification We use the Cooperative Patent Classification (CPC) to determine the technology class of each patent. The CPC system applies a five-level hierarchical system: (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 subset analyzed in Figs. 1 and 2 is associated with 6.0 classification codes per patent on average. For calculation of cosine similarity and pivot size, we pool together the classification codes associated with each reference.

S1.3 Scientific grant data

We also use scientific grant data from Dimensions. Dimensions collects over 5 million granted projects from over 600 funders across the world. For each project, the data includes the project title, investigators, funder, funding amount, internal project number from the funder, and project duration. Name disambiguation for the investigators and publication authors shares the same ID system in Dimensions, allowing us to examine the funding situation of each author. Here we focus on all grants with end dates no earlier than 2019 to approximate the set of recently funded investigators/authors. In addition, Dimensions combines funding and publication records as well as text mining from acknowledgement statements to infer whether a paper is supported by a funder or a specific grant.

S1.4 Patent references to science

Going beyond paper-to-paper citations, we measure the patent impact of scientific papers using Reliance on Science data[10] (v34). The original linkage contains 40.4 million citation pairs from worldwide patent documents to scientific papers indexed in the Microsoft Academic Graph (MAG). In our analysis, we focused on USPTO patents. We further merge the cited papers to the

Dimensions database using DOI. Together, these steps yield 4.1 million Dimensions papers with at least one USPTO patent citation.

S1.5 Market value of patents

Data for the market value of patents is from Kogan et al. (2017)[7]. Their study considers stock price reactions on the day patents are issued to the relevant firm. Using an event study design, they produce a market valuation for each patent. This method, and hence the data, only applies to patents from publicly traded firms. Market valuations and pivot size are available for 802 thousand patents issued over the 1980-2015 period.

S2 Methods

S2.1 Individual careers

Our analyses focus on the pivoting behavior of researchers and resulting impact. To measure pivoting behavior, we need a stream of work by that researcher so that a given work can be compared to the prior work of that researcher. We therefore focus on researchers who have at least 5 works. Any papers for which a researcher is an author, including coauthored papers, are considered part of that person's stream of work. Similarly, coinvented patents are attached to each coinventor. For papers, the resulting dataset includes 37 million papers over the 1970-2020 period. For patents, where inventors tend to be less prolific and having at least 5 patents is not as common, the resulting dataset includes 1.8 million patents over the 1980-2015 period. For both papers and patents, we use the name disambiguated identifiers provided by our data sets (see above).

Given the body of work assigned to each researcher, we further calculate several relevant metrics. These include career age, which is measured as the number of years since the author's first publication year (or, for inventors, the number of years since the first patent application year). We further calculate the citation impact of each researcher's individual works, their modal field of research, their number of publications, and their typical pivot size. These characteristics can be further used to define control groups when studying how researchers respond to external events.

S2.2 Pivot size

We calculate pivot size as described in detail in the main text. Figure 1 presents the pivot size distributions for papers (Fig. 1b) and patents (Fig. 1c). Here we consider additional assessments of pivoting behavior and pivot size distributions, using alternative classifications in the data, and further demonstrate the robustness of the pivot penalty to alternative approaches.

S2.2.1 Papers

For papers, our main analyses use the prior three years of publications by a given author to calculate pivot sizes for any given paper. One can alternatively use all the prior works of the author, at the given point in the career, to calculate pivot sizes. Extended Data Fig. 10 presents the pivot size distribution using the full list of prior work and shows that pivot size distribution remains similar. Further, the pivot penalty continues to appear (Extended Data Fig. 10). As an additional robustness test, these further analyses also examine COVID-19 research and continue to find similar findings as when using the three-year window.

An alternative and substantially coarser way to calculate pivots for papers is to use fields instead of journals. Specifically, one can code a paper's references not by their journal but by their L1 field code and then rebuild the pivot measure for each paper on this basis. This is a much coarser approach, in the sense that there are 154 L1 fields, while there are 40,225 journals. In terms of the number of fields, coding papers in this coarser way is akin to the level-two CPC coding variant for patents (see below).

Fig. S3 compares pivot size as measured using L1 field codes with pivot size when measured using journals. We see a monotonic positive relationship. Note also that, using the field codes, the pivot measure is compressed to lower values, with a pivot size above 0.5 accounting for only 5 percent of papers. This leftward shift in the pivot size distribution is natural when using a coarser knowledge coding, as shifts in referenced fields are bigger and rarer. Fig. S3 further shows that we continue to see a pivot penalty when using L1-field codes to define pivot sizes, with the pivot measure compressed to lower pivot sizes. The main text features the journal-based analysis, both because it shows greater range in pivoting and because of known concerns about the quality of field encodings in paper data (Bornmann 2018), which may lead to noise and attenuation when relying on the field encodings.

Table S10 provides an illustrative example of pivot size for three authors with different pivot sizes. To provide a common context, we consider focal papers related to COVID-19, all published in 2020. We present the focal COVID-19 paper and its title, together with three papers for each author from the prior three years. The examples consider a researcher with a large pivot (0.95), a researcher with a middle-sized pivot (0.51) and a researcher with a relatively small pivot (0.18).

S2.2.2 Patents

For patents, one can draw on the hierarchical nature of CPC technology classification to re-examine pivot sizes and the robustness of the pivot penalty. Extended Data Fig. 4 shows that, as one shifts from the narrowest technology classification (level-5, with 210,347 subgroups) to the broadest (level-1, with 9 sections), the pivot distribution for inventors shifts leftward. As with papers, coarser field classifications naturally result in leftward shifts in the pivot size distribution. Nonetheless, pivoting behavior remains highly variant. Fig. S1 further shows that, regardless of the technological classification used, the pivot penalty is robust in all cases. Thus, for the papers and patents, the fundamental finding of a pivot penalty endures regardless of numerous alternative coding schemes for areas of knowledge.

A distinction for patents, compared to papers, is that the pivot size distribution appears bimodal, with a tendency towards very small pivots and very large pivots, and indeed this feature endures using broad or narrow field encodings (Extended Data Fig. 4). The high frequency of large pivots (near 1) is due in part to cases where there are relatively few references in prior art from a given inventor. This could occur either because the inventor has few prior patents or because that inventor's prior patents make few prior art references. To further investigate this dimension, Fig. S4a presents the patent pivot size distribution when we restrict the sample to inventors with at least 10 patents in the prior three years. Fig. S4b further presents the patent pivot size distribution when we restrict the sample to inventors with exactly one patent in the prior three years but then separate out cases where that patent has at least 100 prior art references. We see that in both cases the presence of very high pivot patents declines substantially. That said, the bimodal nature of the patent relationship still remains and appears robust to these reference count considerations. A substantive reason for the bimodal behavior of inventors may be that inventors in patenting contexts are often assigned to their research directions. For example, based on the corporate priorities, inventor R&D groups may be asked to engage new areas (high pivots) or double down on existing areas (low pivots) following the direction of R&D management and the interests of the firm.

S2.2.3 Manual checks for high pivots

We studied high pivots to see if very large pivots may be related to any name disambiguation issues. Specifically, we took a random sample of 10 authors who produce a paper with a pivot score >0.95 in the year 2020. We then took this very high pivot paper (10 papers) as well as all other papers in the database that were associated with that author and published over the prior three years (totaling another 148 papers). We then hand checked every paper associated with these authors against the authors' CVs, personal websites, Google Scholar profile, PubMed page, or Scopus page (depending on the source available for a given author). The large majority of the 158 papers, including all 10 very high pivot papers, could be verified as matches through the authors' own CVs/websites/Google scholar etc. profiles. The very high success rate gives further confidence that name disambiguation is sufficiently accurate. See Section S3.1 below for further analysis and detail.

S2.3 Impact measures

S2.3.1 Main citation based measure

Our primary measure of paper impact is an indicator for whether an article is in the 95th percentile or higher of citations compared to articles published in the same year with the same L1 fields. Similarly, we define a measure of patent impact by looking at whether a patent is in the 95th percentile or higher of citations compared to patents in the same year with the same primary class. This approach provides a binary outcome variable, where 1 indicates a high impact work and where the mean hit rate is 5% by construction in any given field and year in the data. As such, this method normalizes the outcome across different fields and across different periods of observation.

S2.3.2 Alternative citation based measures

Our main analyses focus on a binary indicator for being especially high impact, with two primary motivations. First, scientific and technical progress may hinge on key, high impact ideas, and second, theories of creative search (such as explore vs. exploit frameworks, or emphases on creative outsiders) often orient on the production of high-impact ideas. When looking within individual careers, however, high impact work can be rare, and many individual researchers do not produce high impact works. Thus, smoother outcome measures of impact may be useful especially when looking within individual careers, as well as for providing robustness checks on broader findings. We therefore consider numerous additional citation measures, which can be used to further characterize results.

Mean citations. As a smoother measure of the citation impact, and following prior literature, we take a paper's citation count and normalize it, dividing by the mean citation counts for papers in that field and with the same publication year[8,9]. This approach allows for a more continuous measure of impact while also continuing to normalize for citation differences across fields and time. Extended Data Fig. 3a shows that the pivot penalty remains large using this more continuous measure. Specifically, the citation impact of the lowest pivot papers tends to be approximately 30% above the field-year mean while the citation impact of the highest pivot papers tends to be approximately 55% below the field-year mean.

Mean percentile citations. Another approach to measuring impact converts each paper to its percentile of citations received among all papers published in that field and year. This provides another, smoother version of citation impact compared to the binary measure, while also limiting the influence of any outliers. Extended Data Fig. 3b shows that the pivot penalty continues to appear and remain substantial using this alternative measure. Specifically, the lowest pivot papers on average are in the 58th percentile of citations received compared to other papers in the field and year, while the highest pivot papers on average are in the 36th percentile.

Time frame. Comparing works published in the same field and year acts to normalize the measure of citation impact. That is, citation impact is always being compared among papers in the same field and with the same horizon for citation (between the publication year and the present).

However, one can also use a fixed period after publication as an additional way to normalize the time frame. We recompute citations received by each paper using, alternatively, two-year, five-year, and ten-year forward windows. Extended Data Fig. 2 shows that the pivot penalty is similar regardless of these alternative citation windows.

Alternative binary indicators. Within the class of binary indicators, which are useful to emphasize the locus of the highest-impact work, one can consider alternative percentile thresholds. The main analyses consider papers with citations received in the 95th percentile or above. Alternatively, we consider indicators for work in the upper 90th, 95th, 99th, 99.5th and 99.9th percentile of citations received. Fig. S5 shows that the pivot penalty remains severe at these different impact thresholds, and indeed high-pivot work is even less likely to achieve the higher impact thresholds compared to low pivot work, as discussed in the main text.

S2.3.3 Non-citation based measures

Journal placement. When examining research in 2020 (including COVID-19 research) there has been less opportunity for works to accumulate citations. We therefore use journal placement as an alternative. For the journal impact measure, we mirror the baseline citation measure by calculating the share of papers in a given journal that reach the 95th percentile of citations (within its field and year), averaged between 2000-2019. This metric is intended to infer both the likelihood of becoming a hit paper and the authors' perception of a paper's impact and contribution based on journal placement.

Publication success. Our datasets consider published papers and granted patents, following standard practice in analyzing science and innovation outcomes. However, for recent years in science, we can also take an additional step by using preprints and asking whether preprints ever become published. Specifically, we examine all 1.07 million preprints released from 2015-2018 on preprint databases such as arXiv and SSRN. We define an indicator variable that is equal to 1 if the working paper becomes a published article in our data.

Extended Data Fig. 6 shows that higher pivot sizes are associated with a large decline in the probability of being published. There is a smooth decline in publication propensity with pivot size, where virtually all of the lowest-pivot size working papers become published while only two-thirds of the highest-pivot papers are published (within five years). Thus, not only do higher pivots exhibit declining impact, conditional on publishing, high pivots are also harder to publish. The impact challenges of high pivot appear only stronger from this additional viewpoint. For example, taking $\Pr[\mathrm{Hit}] = \Pr\,[\mathrm{Hit}|\mathrm{Published}] \times \Pr[\mathrm{Published}]$ (where we note that unpublished papers cannot be hits), the highest-pivot papers would see unconditional hit rates that are approximately two-thirds lower than the (already low) hit rate conditional on successfully publishing. This method of observing preprints that fail to publish opens new avenues of insight in the science of science that may be used in other studies.

Patent usage of science. As an outcome measure for a given scientific work, we further consider whether the article is referenced as prior art in a future patent. This outcome indicates applied use of the scientific ideas, suggesting an important form of impact that occurs beyond the domain of science itself [10,11]. For each scientific article, we use a binary indicator where 1 indicates that the article is directly referenced in a future patent. Extended Data Fig. 5 shows that high-pivot papers are substantially less likely to be referenced in a future patent. The pivot penalty is not monotonic in this case, with low pivot sizes associated with less applied use. However, this outcome measure is not normalized by scientific field (unlike the citation impact measure in science), and there is substantial heterogeneity across scientific fields in the frequency of direct patent citations[11]. For example, nanotechnology papers are far more likely to be cited in patents than astrophysics papers are. To absorb field heterogeneity, we further consider patent citations to science in a regression with fixed effects for the paper's L1 research field. The result, shown in Extended Data Fig. 5, indicates that the non-monotonicity at low pivot sizes largely disappears with this simple field control.

Market value. As an outcome measure for a given patent, we consider the market value measure[7], which assigns to a patent a market value based on the stock price response of the business on the day of the patent's issuance. This measure is only available for patents that are assigned to publicly held firms. Extended Data Fig. 7 shows that higher-pivot patents have substantially lower market value.

S2.4 Tail novelty and median conventionality

Following the existing literature, we measure the novelty and conventionality of academic papers by considering the combinations of existing ideas.[12] We consider the pairwise combinations of journals cited by each paper and compare them to the expected frequency that those combinations would appear by chance according to the existing network of citations. Two journals that are unlikely to be paired by chance indicate a novel combination, while journals that are more likely to be combined indicate a conventional combination. Specifically, a journal combination can be assigned a z-score, comparing the observed and expected frequency of that journal pairing in science and normalizing by its standard deviation. Each paper has a distribution of z-scores across all the journal pairs it references. Following prior literature, we denote a "high tail novelty" paper if its 10^{th} percentile z-score is below 0, and we denote a "high median conventionality" paper if its 50^{th} percentile z-score is in the upper half of all papers.[12] Past literature suggests that high impact papers typically have both high tail novelty and high median conventionality. Much of the work that those papers build on is rooted in conventional knowledge combinations but sprinkles in new combinations of existing knowledge as well[12]. In this paper, we use a pre-calculated version of novelty and conventionality provided by SciSciNet, an open source database[13].

Extended Data Fig. 8 shows that higher pivot papers tend to make novel combinations. This indicates that when researchers pivot, they are not only being novel in their own terms, compared to their own portfolio of research, but they also tend to introduce combinations that are novel in science as a whole. By contrast, high pivots are associated with low conventionality. Thus high-pivot work tends not to feature the grounding in conventional combinations that are a key combinatorial ingredient in predicting high impact work. Table S9 further considers regression analysis of pivoting behavior, novel combinations, and conventional combinations together. These regressions continue to show a substantial pivot penalty. Thus, while high pivots are strongly associated with low conventionality, regressions put the weight of impact on pivoting.

S2.5 New collaborators

To track a scientist's engagement with new collaborators over time, we first construct a set of collaborators for each author-paper pair, tracking coauthorship interactions among all the disambiguated authors in the author set (see S2.1). We then sort all publications in one's career by publication date and sequentially calculate the number of new collaborators in each paper.

To further understand the characteristics of these new coauthors, we calculate their major field of research (both level-0 and level-1) before the paper's publication year. We also compare the affiliation information of new collaboration pairs (based on disambiguated GRID ID) to see if the focal author and collaborator share at least one common affiliation. Together, these measurements allow us to count the number of new collaborators, as well as whether new collaborators come from the same or different field or affiliation. If either the focal author or the collaborator has missing data in field or affiliation, this pair is considered as "unknown" and excluded in the same/different categorization.

S2.6 Regression methods

S2.6.1 Output level analyses

Our most basic analyses consider the output level, where an observation is a given work (paper or patent) and where pivot size used is the mean pivot size among the members of the team. These regression models in general take the form:

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

where i indexes a given work (paper or patent), $Impact_i$ is one of the various outcome measures (see above), and $\boldsymbol{X_i}$ is a vector of control variables. Rather than imposing a linear or other functional form on the data, we write $f(Pivot\_size_i)$ to emphasize potentially general functional forms for the relationship between pivot size and impact.

To reveal potentially non-linear relationships between pivot size and outcome variables, many analyses use binned scatterplots[14]. In Fig. 2a for example, we order the sample of papers by average pivot size along the x-axis and split the observations into 20 evenly-sized groups. Then each marker is placed at the mean (x,y) value within each group. Similarly, in Fig. 2c, we consider the same using patents.

We also extend the binned scatterplots analysis to include control variables. For example, for the multivariate regression results presented in Fig. 4k, we consider numerous additional controls, including fixed effects for average prior impact groups, author age groups, team size, the number of new collaborators, and an indicator variable for whether the paper was funded. To include regression controls while maintaining the non-parametric advantages of the binned scatterplot approach, we in practice run two regressions to residualize pivot size and impact, net of the controls, following the Frisch-Waugh-Lovell theorem. Specifically, we first run regressions of the form:

$$\text{PivotSize}_i = \alpha_1 + \boldsymbol{\theta_1 X_i} + \varepsilon_{1i}$$

$$\text{Impact}_i = \alpha_2 + \boldsymbol{\theta_2 X_i} + \varepsilon_{2i}$$

And then consider the binned scatterplot relationship between residual impact ($\widetilde{\text{Impact}}_i = \text{Impact}_i - \hat{\alpha}_2 - \boldsymbol{\hat{\theta}_2 X_i}$) and residual pivot size ($\widetilde{\text{PivotSize}}_i = \text{PivotSize}_i - \hat{\alpha}_1 - \boldsymbol{\hat{\theta}_1 X_i}$).

Finally, when looking at subsets of the data to test the robustness of a negative slope between pivot size and impact, we also consider the linear version of the baseline regression, taking $f(Pivot\_size_i) = \beta Pivot\_size_i$. For example, we run this regression separately in each L1 field for papers, and in each CPC patent class to test how often the negative slope of the pivot penalty appears. See Tables S1 and S2.

S2.6.2 Researcher panel level analyses

To examine the relationship between pivot size and impact within individual researchers, we use a panel data structure. Observations are at the researcher-by-paper and researcher-by-patent level, which allows the inclusion of individual fixed effects. By including individual fixed effects, the regressions compare variation in impact within the individual against variation in pivot size within the individual. More generally, the individual fixed effects account for any fixed characteristic (observed or unobserved) for a given researcher. We will also use this panel structure, with individual fixed effects, when considering the natural experiment described further below.

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

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

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[15]. Standard errors are clustered at the researcher level.

To analyze pivoting in more specific contexts, we take subsets of the data. For example, to shed light on reputational mechanisms, we consider the subset of data where an author has multiple papers in the same year in the same L1 field, or in the same year and in the same journal. Table S4 presents these results. To consider the effects of external shocks we take the subset of treated and control researchers (see next section).

S2.7 Difference-in-differences methods

When studying external shocks, we continued to use the researcher panel data model with individual fixed effects. We implement standard difference-in-differences 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-c. We also show "event study" style difference-in-differences plots in Fig. 3d-e, 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. In addition to the reduced form results, we also consider the two-stage-least-squares estimate, where $Treat\_Post_{ipt}$ instruments for $Pivot\_Size_{ipt}$ (Tables S6-7). As with other researcher-level panel analyses, standard errors are clustered at the researcher level. We next describe specific details of the retraction experiment, including definitions of the treatment and control groups.

S2.7.1 Retractions analysis

In the retractions analysis, we start with 13,455 papers that were retracted (see SI Section S1.1). Treatment timing is the year of the retraction for each paper. The idea here is that the retraction event for a given paper devalues that research. Scientists who had been drawing on the retracted work may naturally move away from that line of research. The treatment group consists of those authors who had cited the retracted paper at least once in the period between the paper's publication year and the year prior to its retraction but were not themselves an author of the retracted paper. We do not include authors of the retracted papers themselves because these individuals may experience direct effects from the retraction. By contrast, those who had cited the retracted papers can be seen as utilizing work that then appears to have shakier foundations, potentially provoking shifts in the direction of their research. We further analyze the treated group based on how many times the treated authors cited the retracted paper, prior to its retraction. This provides a natural way to consider the intensity of treatment, where authors who were building more regularly on the retracted work may naturally undertake a larger move. Among the treated authors, there are 164,988 authors who cited the retracted paper at least once prior to its retraction and 18,505 authors who cited the retracted paper at least twice.

To build the control group, we consider all authors who cited other publications in the same journal and publication year where the (eventually) retracted paper was published. We then remove from this set any treated author. Among these control authors, we further use coarsened-exact-matching (CEM) so that the control authors match closely to the treatment authors prior to the treatment year in their publication count and rate. There are 162,793 control authors.

In addition to the analyses in Fig. 3 of the main text, Table S6, Fig. S6, and Fig. S7 consider alternative specifications. Table S6 first considers alternative outcome measures, where impact is measured as (a) the hit rate of the paper using only the first two years of citations after publication or (b) the citation count of the paper in ratio to the field-year mean. Table S6 further considers two-stage-least-squares estimates, with retractions as the instrument. Fig. S6 considers event study plots defining treated authors as the larger set of those who cited the retracted at least once prior to retraction. Fig. S7 further considers event study plots using alternative impact measures, examining hit rates and citations counts when observed over a two-year window. These analyses all further support the findings in Fig. 3.

S2.7.2 Psychology analysis

We consider a similar but much smaller natural experiment using replication failures in psychology. Namely, a landmark replication analysis[16] quasi-randomly selected 100 psychology publications from 2008 and tested them for reproducibility. Of the tested papers, 64 had results that failed to replicate, providing the core for our treatment group. Treated authors are those who had repeatedly cited a non-replicating 2008 paper, prior to the replication analysis, but were not themselves an author of the non-replicating paper. As above, we do not include authors of the non-replicating papers themselves because these individuals may experience direct effects from the failure to replicate. By contrast, those who had repeatedly cited the non-replicating papers can be seen as utilizing work that then appears to have shakier foundations, potentially provoking shifts in the direction of their research. There are 843 treated authors. To build the control group, we take all authors who cited other papers in the three psychology journals and publication year chosen for the replication study (but who did not cite any of the papers in the replication analysis). Among these authors, we use coarsened-exact-matching (CEM) so that the control authors match closely to the treatment authors prior to the treatment year in their publication count and rate. Table S7 presents difference-in-differences estimates for this psychology study.

S2.8 COVID-19 analyses

COVID-19 provides another kind of external shock that may encourage pivoting. In contrast to the "push" shock of retractions, where authors may pivot away from research areas that no longer appear reliable, COVID-19 presents an important new object of study, a "pull" shock that may encourage researchers to pivot into this new area. COVID-19 is of additional interest because of its wide societal import and the opportunity to understand how science as a whole pivots to engage a critical new area. Because the shock is to science as a whole, as opposed to specific researchers (as with retraction events), we cannot deploy a natural experiment in the same framework as with retractions. Nonetheless, we can compare researchers who pivot with observationally similar researchers who did not pivot, and we can compare within a given researcher their COVID-19 work with their own other work, to inform how science responds to a critical global shock.

In Fig. 4c, we focus on a subset of COVID authors and non-COVID authors that share similar characteristics. Specifically, these career comparison graphs focus on scientists who first published in 2005. The COVID scientists here are the 6,406 authors among those who first published in 2005 and who published at least one COVID publication in 2020. We then match these authors to a control group of non-COVID scientists that also started their publication career in 2005 and have the same primary level-1 field. For each COVID author, we use a nearest-neighbor match on the number of publications between 2015 and 2019 (sampling without replacement) to construct a control group that also includes 6,406 authors.

We further analyze impact with and without control variables. Fig. 4e considers binned scatter plots, comparing COVID and non-COVID research, without control variables. In Fig. 4g-h and Fig. 4j, we split the COVID and non-COVID samples into groups based on the median team size, number of new collaborators, and whether the paper was connected to a funding source.

For the wide-ranging multivariate regression results presented in Fig. 4k, we include additional controls. The additional controls include fixed effects for average prior impact groups, author age groups, team size, the number of new collaborators, and an indicator variable for whether the paper was funded. In Fig. S8, we include individual fixed effects, or in other words control for all fixed characteristics associated with each author. In this individual fixed effect analysis, we are considering researchers who produce both COVID papers and non-COVID papers in 2020, thus allowing comparison of outcomes and pivoting within individuals who respond to the pandemic and comparing outcomes within their contemporaneous body of works.

S2.9 Pivots and moderating factors

The main text considers potential moderating factors that might facilitate successful pivots. The analyses are informed by the science of science literature [67-69]. Here we provide background on the different dimensions considered, and provide additional analyses.

First, it is sometimes posited that younger scientists are more likely to engage novel research streams or more capable of producing novel and high-impact ideas, in accordance with Planck's Principle [17, 19] or a more general creative aptitude among the young [58]. However, we find that the pivot penalty appears among both older and younger researchers (Table S5). Thus, while creative orientation, skills, and other resources or capabilities may vary according to a researcher's career stage [17, 19, 58], the pivot penalty appears persistently within different career stages.

Second, teamwork may be a critical feature in facilitating adaptability. Not only are teams increasingly responsible for producing high-impact and novel research [28, 33, 41, 70], they can also aggregate individual expertise [15], extending an individual's reach and promoting subject-matter flexibility [29, 71]. Looking to the pandemic, we find that team size was larger for COVID-19 papers than is typical in the respective field. Compared to field means, COVID-19 papers see 1.5 additional coauthors on average (a 28% increase in team size, Fig. S9). Further, COVID-19 authors work to an unusual degree with new coauthors (Fig. 4f), rather than existing collaborators, and engaging new coauthors is associated with larger pivots (Fig. S10). These results are consistent with teamwork expanding reach [15, 72, 73]. Nonetheless, we again see the pivot penalty in both large and small teams, and in teams with and without new coauthors (Fig. 4g-h). Thus, while bigger teams and teams with novel coauthors appear to predict higher impact, the pivot penalty persists.

Finally, we further probe adaptability through the lens of funding. We integrate funding data from Dimensions, which incorporates 600 funding organizations worldwide, and identify grant-supported research in 2020 for COVID and non-COVID papers (Fig. 4i). We see that grant-supported research disproportionately features small pivots. Specifically, there is a large and monotonic decrease in grant-supported research as pivot size increases, and this relationship is especially pronounced for COVID-19 papers, which are less likely to cite a funding source across all pivot sizes. These findings are natural to the extent that funding supports specific agendas, so that large pivots in general, and COVID-19 pivots in particular, tend to occur without acknowledging specific grants. Nonetheless, returning to impact, we find that the pivot penalty persists whether the paper does or does not acknowledge a specific grant, both in science as a whole and among COVID-19 research (Fig. 4j).

Altogether, one can consider numerous potential moderating factors and forms of heterogeneity, including individual's career stage, project-level team size, the use of new coauthors, and funding. When examining impact, however, we find that the pivot penalty persists regardless of these features. We further use regression methods to incorporate detailed controls for many features together (see SI S2.6), finding that net of all these features, the pivot penalty remains substantial in magnitude (Fig. 4k).

S3 Additional analyses

S3.1 High pivot cases

Cases of high pivots might potentially be an artifact of name disambiguation, where two different people are conjoined into one record but work in different areas. One test for this is to hand-check high pivot cases, comparing database results against public CVs. To proceed, we took a random sample of 10 authors who produce a paper with a pivot score >0.95 in the year 2020. Of these 10 authors, 5 were randomly chosen from authors with the 200 most common names, and 5 were randomly chosen from authors with uncommon names. For each author, we then took their very high pivot paper (10 papers) as well as all other papers associated with that author in the database that were published over the prior three years (totaling another 148 papers). We then hand checked every paper in the database associated with these authors against the authors' own CVs, personal websites, Google Scholar profile, Scopus page, or PubMed page (depending on what source was available for a given author).

The results of this manual verification were as follows. First, for the 10 very high pivot papers, we found each paper on the authors' own CVs/ websites / Google scholar etc. profiles. Thus, all the high pivot papers appear correctly assigned to these authors. Second, examining the prior works of these authors, for 9 of the 10 authors we located 100% of their prior papers in

Dimensions on the authors' public profiles. For the remaining author, who is located in China, we could verify 27 papers (80%) on the author's Scopus and PubMed profiles, where the other 7 papers in Dimensions were in Chinese-language journals; these match on name and field of the author but are not listed in the extant English-language profiles, so we could not confirm that Dimensions was correct, or incorrect, for these 7 papers. In sum, this manual verification exercise suggest that all the high pivot papers were correctly assigned to these authors, and we could confirm 96% of the works of these authors are also correctly assigned, while the other 4% of papers had clear matching characteristics but we could not verify the match against other profiles. The very high success rates matching these authors' works by hand gives further confidence that name disambiguation is sufficiently accurate. A spreadsheet detailing the hand curation exercise for each of the 158 papers analyzed is available from the authors upon request. Another approach, which can be scaled across the data, is to analyze generally common names and rare names. The idea is that researchers with common names may pose greater challenges for name disambiguation, which in our case would be revealed as showing larger apparent pivot sizes. To proceed, we take all papers published in 2010. We then plot a binscatter relating mean pivot size to surname frequency (Fig. S11). While we see some variation, overall the relationship is quite flat, with the most common surnames showing similar pivot sizes as seen among relatively uncommon surnames. We further consider the pivot penalty relationship, separately for both individuals with the most common surnames and, separately, among other authors (Fig. S11). We see that the pivot penalty appears in both groups. Overall, these additional analyses further increase confidence in name disambiguation and the robustness of the findings.

S3.2 Outlier fields

Table S1 Panel a indicates that a large majority (93.5%) of the 153 fields with at least 20 papers show a negative correlation between pivot size and impact. Here we investigate the 6.5% of fields (10 fields) that do not show this negative correlation.

An initial observation is that these outlier fields are relatively small. Although these 10 fields are 6.5% of fields, they collectively incorporate only 0.18% of papers. Table S8 lists these 10 fields, together with their observation counts, and the slope and its standard error when relating pivot size and impact. Of the ten fields, five show a statistically significant relationship. One of these "Other Built Environment and Design" has only 87 papers.

Another important observation is that the outlier fields have characteristics that may make the pivot measure less salient in these specific contexts. Specifically, there are notable field commonalities. First, the only field with a highly statistically significant positive relationship is "Visual Arts and Crafts," and the field Art Theory and Criticism also exhibits a positive (but non-significant) relationship. One interpretation is that art-oriented fields privilege pivoting, but these are also fields where books are a main avenue of output and references, and thus our journal-reference pivot measure may be less salient in defining reference and pivoting behavior. Second, the largest three outlier fields in size are all computer-science related fields. These are relatively small subfields of computer science; the larger computer science fields exhibit the usual pivot penalty. Further, computer scientists rely heavily on conference proceedings as key venues for their work. In publication databases each conference proceeding acts as a different journal in each year. This may lead to apparent high pivots as these "journals" come and go, making the pivot measure less salient, while at the same time these conference proceedings can be associated with high impact new work in computer science.

One may further consider higher level groupings of fields to see if there are any important contrasting areas of research. In Fig. S12, we categorize the L1 fields into 7 higher level groupings, mapping each field into one of medical sciences, life sciences, physical sciences, engineering, social sciences, humanities, and other. As can be seen in the figure, there is some heterogeneity, but these different areas of research all show substantial, negative relationships between pivot size and impact.

Overall, the small minority of fields with the contrasting relationship are those that have relatively low numbers of publications and those where journal-based pivot measures may be less effective in capturing reference and pivoting behavior.

S3.3 Pivoting and field switching in science

The pivot size measurement framework quantities shifts in research direction on a [0, 1] interval, allowing assessment of research shifts in a continuous manner. The method can also be applied using alternative encodings of research areas. In science, we have alternatively studied pivots based on journals as well as field encodings. In patenting, we have alternatively studied pivots using various levels of detail in hierarchical technology class encodings.

One may also be interested in relating the magnitude of pivot sizes, and the pivot penalty, to the case where a scientist switches to a new field. Specifically, one can examine the relationship between the pivot measure (examining the references in a paper) with a binary measure of switching fields (where field codes are assigned to a paper). Fig. S13 shows that when an individual engages a new field, that paper will be associated with a large average increase in pivot size. The top row shows the results for switching to a new L0 field (there are 22 L0 fields), and the bottom row shows the results for switching to a new L1 field (there are 154 L1 fields). Switching to a new L0 field code is associated with moving from a pivot size of approximately 0.5 on average to approximately 0.7 on average. Considering the pivot penalty, such an increase in average pivot size is associated with a hit rate decline by approximately 2 percentage points in recent periods (see Fig. 2). In short, switching to a new field is associated with an approximate 40% drop in the probability of writing a high-impact paper. Note that the quality of the paper-level field encodings in large bibliometric databases is the subject of debate[17,18], suggesting potential noise in measuring field switches, which may in turn attenuate its relationship with pivot size and impact.

S4 Supplementary Information Figures

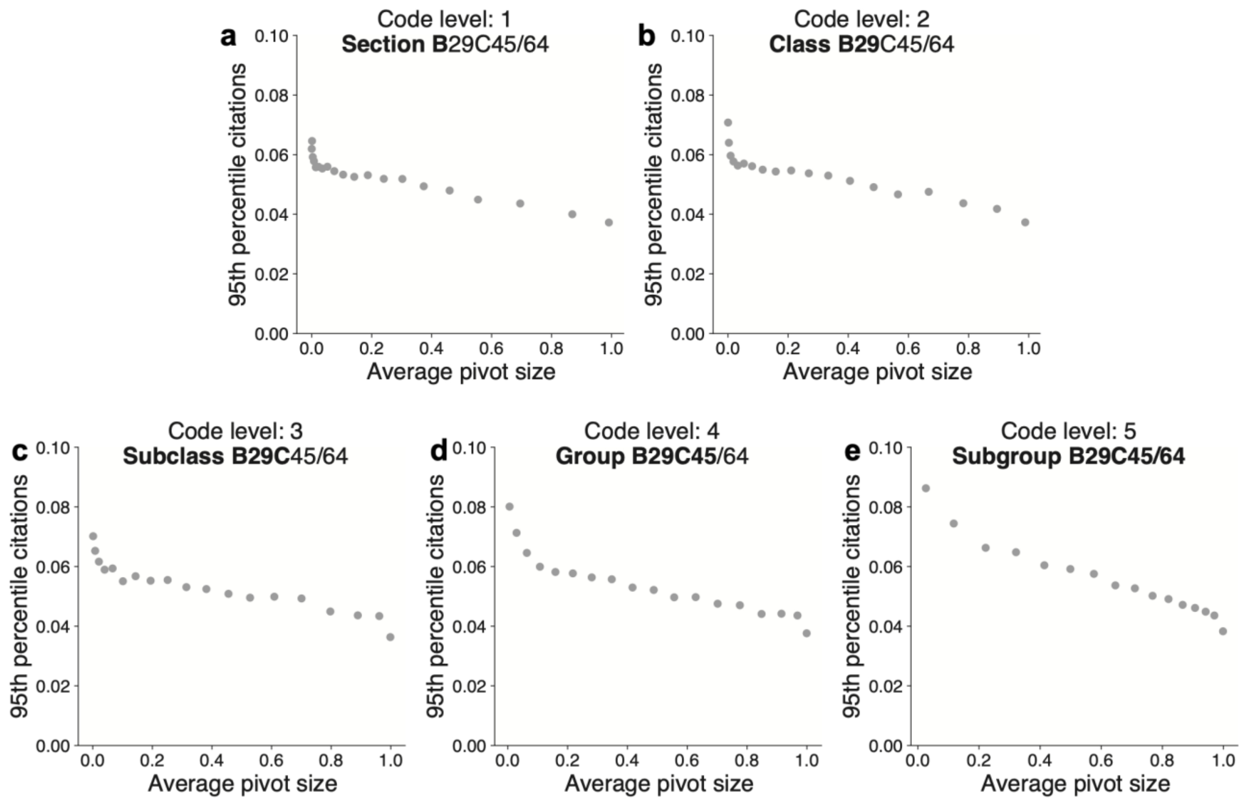

Figure S1: The pivot penalty with various technology levels. The probability of being a highly cited patent is decreasing in pivot size for all technology code levels used to define pivoting (n=1.72 million U.S. patents granted from 1980-2015). The difference in impact between the highest and lowest pivot size is (**a**) smallest when using broad level-1 classes and (**e**) largest when using narrow level-5 subgroups.

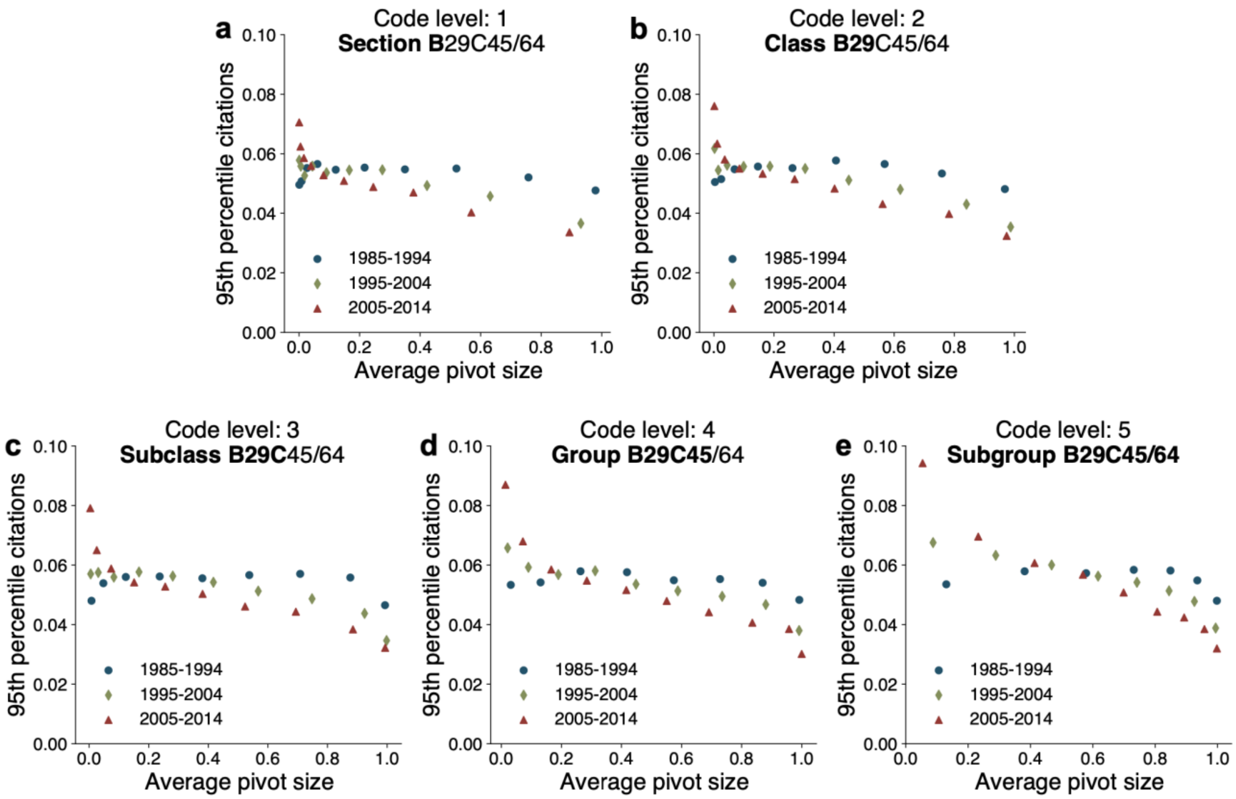

Figure S2: The pivot penalty over time with various technology levels. The slope of the pivot penalty is increasing over time, regardless of which level of technology code is used to define pivot size (n=1.72 million patents). The increase in slope over time is (**a**) smallest when using broad level-1 sections and (**e**) largest when using narrow level-5 subgroups.

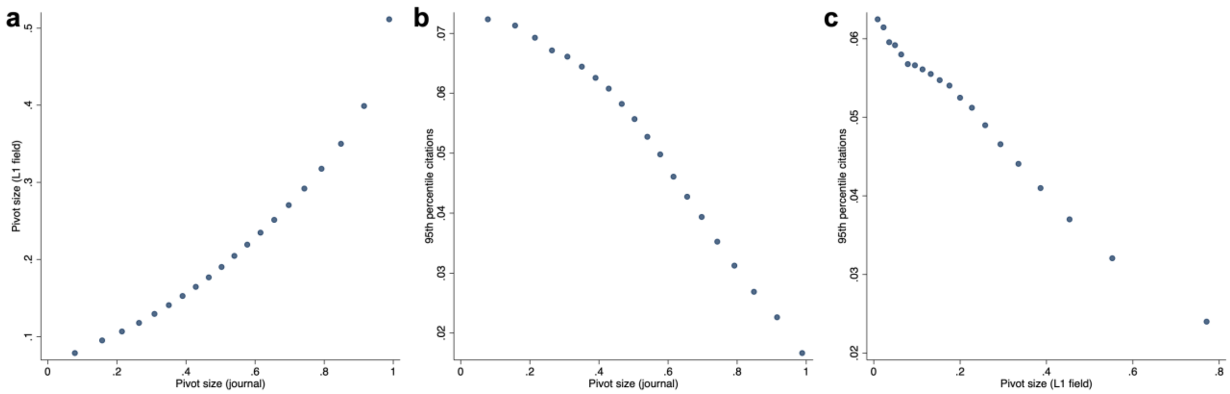

Figure S3: Quantifying pivot size and pivot penalty using L1 field codes. In the main analyses, we use journals cited in reference lists to build the referencing vectors and calculate pivots (n=25.8 million publications from 1970-2015). Here we consider pivots using the L1 fields of the referenced papers, rather than the papers' journals. This is a coarser approach, as there are 154 L1 fields, as opposed to tens of thousands of journals. Panel (**a**) presents the relationship between pivot size using L1 fields and pivot size using journals. We see a positive relationship. We also see a narrowing of the pivot size distribution when using L1 fields, indicating that researchers naturally shift less when the measure uses wider encodings for areas of knowledge. Panels (**b**) and (**c**) present bin scatters relating impact to pivot size. We see the pivot penalty is robust to using the field encoding. Again the distribution of pivot size is substantially condensed, with only a small share of papers having pivot sizes above 0.5. See Extended Data Fig. 4 and Fig. S1 for similar analyses for patents, calculating pivot size using coarser and finer technology classifications.

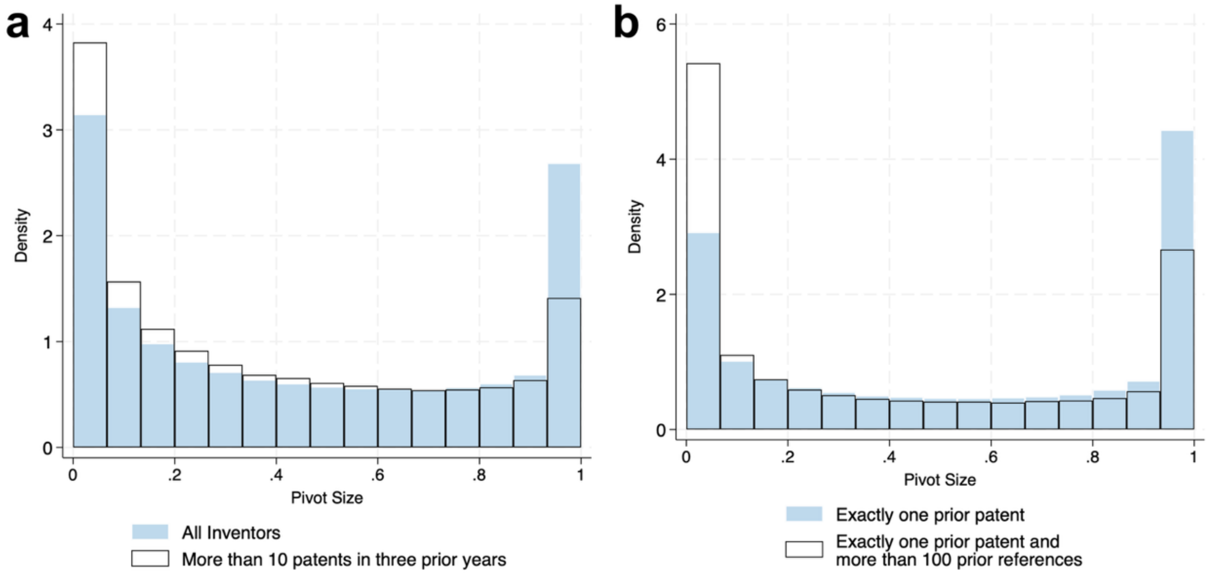

Figure S4: Bimodal pivot distribution for patents. This figure further explores the bimodal nature of the patent pivot size distribution (n=4.2 million inventor-patent pairs published from 1980-2020). The pivot size distribution shifts leftward when restricting the sample to inventors (n=585 thousand inventor-patent pairs) with at least 10 patents in the prior three years (**a**). The pivot size distribution also shifts left when we restrict the sample to inventors with exactly one patent in the prior three years (n=996 thousand inventor-patent pairs), but then separate out cases where that patent has at least 100 prior art references (**b**) (n=202 thousand inventor-patent pairs), While the presence of very high pivot patents declines substantially, the bimodal nature of the patent relationship remains. Thus, the bimodal distribution of patents is not due to cases with a small set of reference material. See Section S2.2.2 for further discussion.

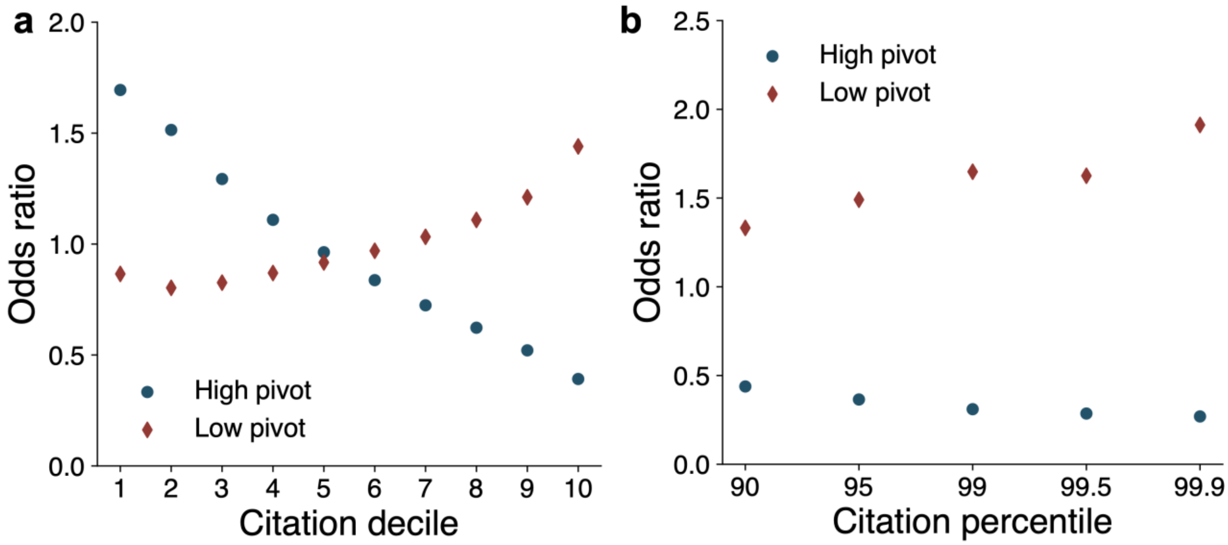

Figure S5: Probability of high and low pivot across citation distribution. (a) The x-axis groups all papers into deciles by the number of citations within year and L0 field (n=34.4 million papers published from 1970-2019). The y-axis reports the odds ratio that a low and high pivot paper will be found in that citation bin. The low (high) pivot odds ratio is calculated as the share of papers in each citation decile that are in the lowest (highest) decile of pivot size divided by the share of all papers in that decile. Papers in the lowest citation decile are almost twice as likely to be high pivot papers than low pivot, while papers in the highest citation decile are almost three times as likely to be low pivot papers than high pivot. **(b)** The x-axis groups all papers into upper percentiles by the number of citations within year and L0 field. The y-axis reports the odds ratio that a low and high pivot paper will be found in that citation bin. Low pivot papers are 3-7 times more likely than high pivot papers to surpass the highest thresholds of impact between the 90^{th} and the 99.9^{th} percentile of citations (n= 3.5 million).

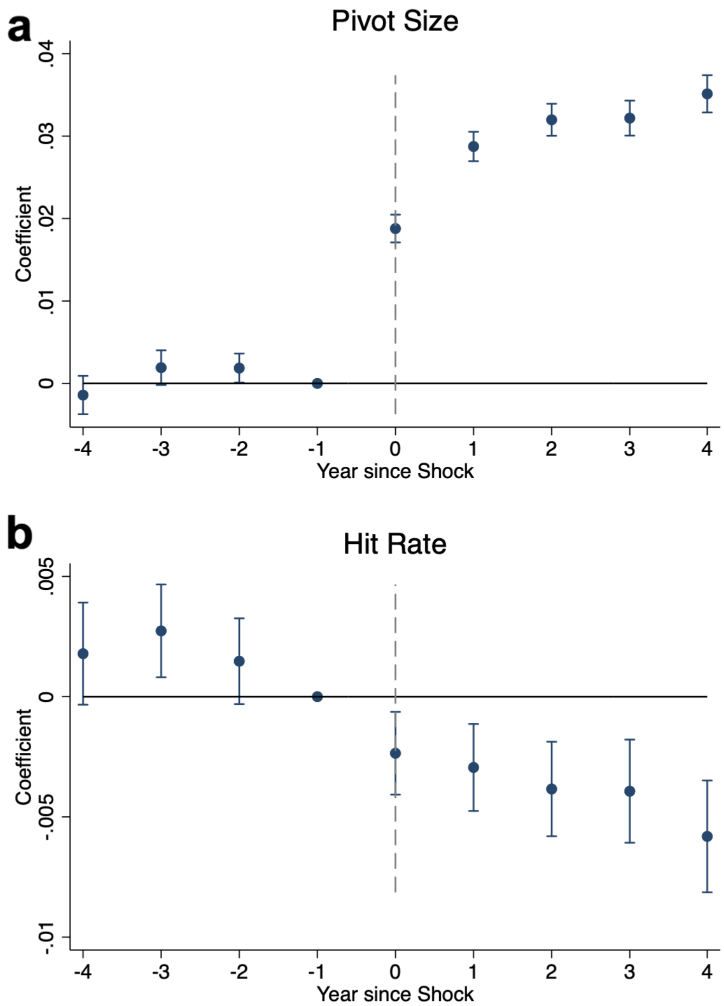

Figure S6: Difference-in-Differences, 1+ reference group. Fig. 3d-e present event study plots for pivot size and hit rate, defining the treated group as those who referenced the retracted paper multiple times. Here we present event study plots for (**a**) pivot size and (**b**) hit rate but now using the broader set of researchers who reference a retracted paper one or more times. We see similar results as in Fig. 3, with an increase in pivot size and a decrease in pivot size after the retraction event.

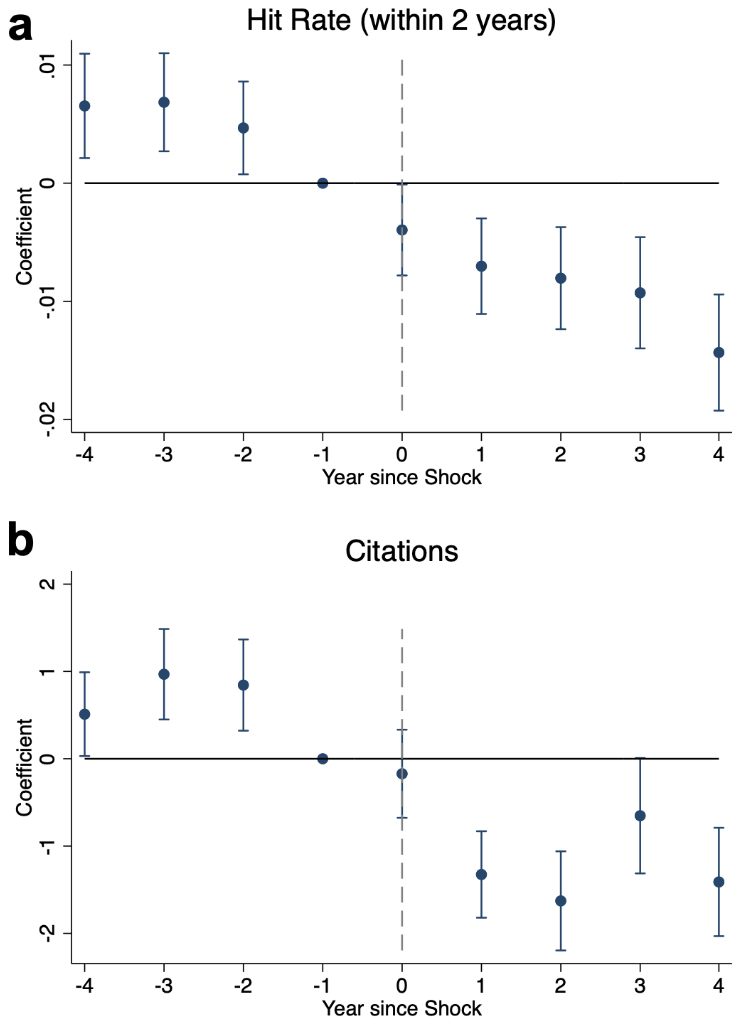

Figure S7: Difference-in-Differences, alternative impact measures. Fig. 3d presents an event study plots where the hit rate is measured using the whole forward citation window after papers' publications. Here we consider alternative impact measures. In (**a**), the hit rate is measured using the first two years of citations after publication. In (**b**), the outcome is a direct citation count over two years after publication. To the extent that retraction events devalue areas of knowledge, these events may reduce references to pre-period works related to the retracted paper. This would cause pre-period paper impact to fall among treated authors, resulting in a conservative bias by making it harder to detect an impact decline for post-period works. Looking at the first two years would mute any effect of the retraction event on citations to the earlier stream. These analyses further support the findings, in addition to acting as robustness tests to time windows more generally.

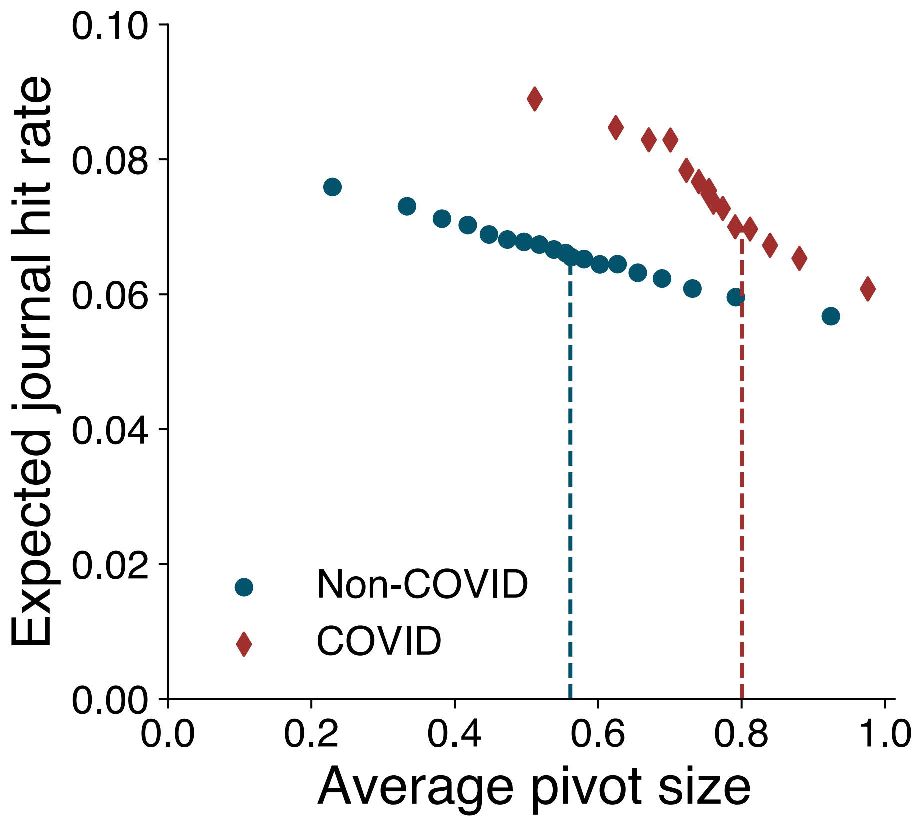

Figure S8: Hit rates and pivot size using individual fixed effects. This figure follows the pivot-impact analysis shown in Fig. 4. In this version, we use a regression adjustment for individual fixed effects within each series to control for unobservable factors that might drive pivot size and impact differentially across researchers (n=3.6 million author-paper pairs from papers published in 2020).

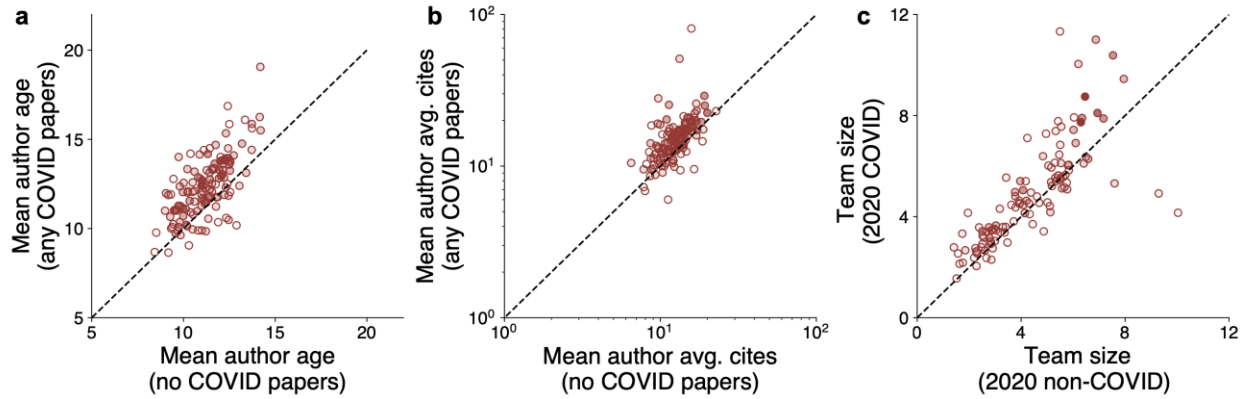

Figure S9: Pivoting characteristics by field. These plots examine paper and author features by field, comparing COVID and non-COVID research among actively publishing scientists in 2020. Markers with darker shading indicate fields with more COVID publications. Authors appear in all level-1 fields in which they published in 2020. Scatter plots include the 130 level-1 fields that had at least 20 authors publish a COVID-19 paper in 2020. **(a)** Mean author age for those who write COVID-19 papers is greater than for those who do not in 82% of fields. **(b)** Mean author prior impact for those who write COVID-19 papers is greater than those who do not in 83% of fields. **(c)** Mean team size is higher for COVID-19 papers in 77% of fields.

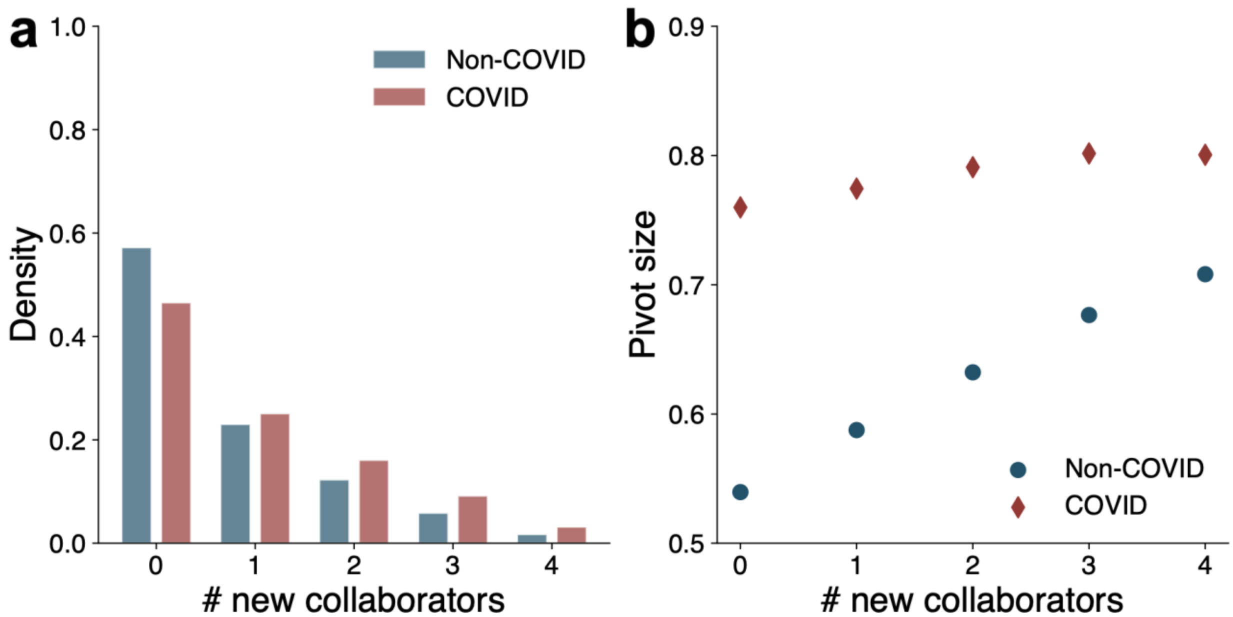

Figure S10: Pivots and new collaborators. These plots consider all 951 thousand 2020 publications with exactly five authors (similar results are found using different team sizes). **(a)** Papers with no new coauthors are the most common form, while **(b)** pivot size is increasing with the number of new coauthors.

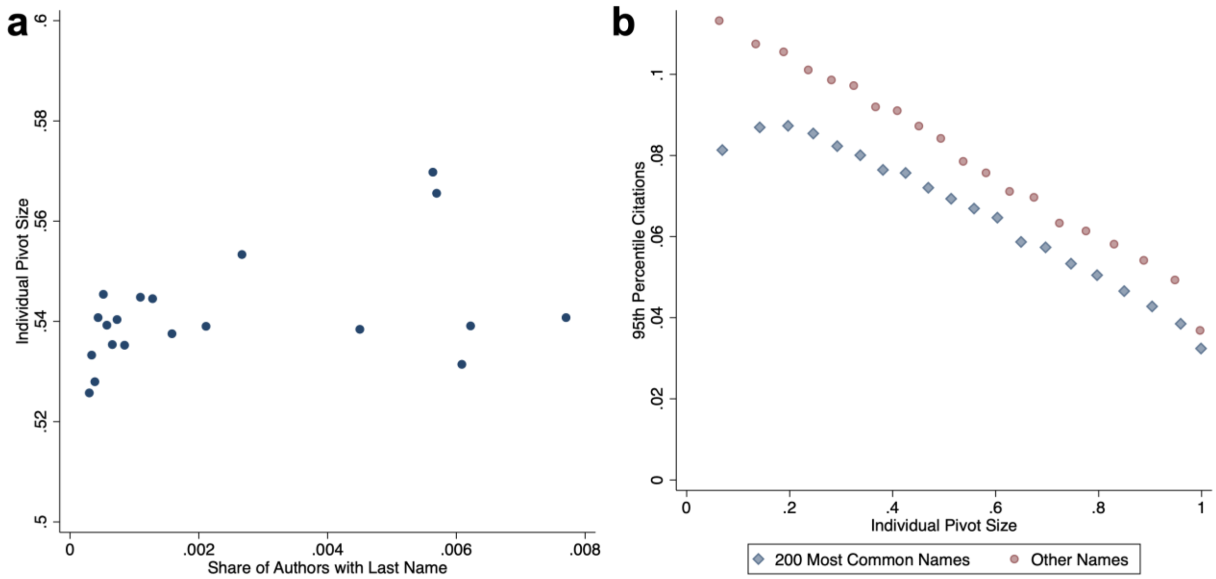

Figure S11: Common and rare names. These figures examine the findings in light of potential name disambiguation challenges. We compare results for scientists with common and rare names, where common names may be harder to disambiguate. Sample is 1.3 million papers published in 2010. (**a**) Mean pivot size as function of surname frequency. This plot shows a bin scatter and indicates little relationship between how common a name is and the mean pivot size for the individual. (**b**) The pivot penalty is robust when analyzed separately among scholars with common surnames or less common surnames. See Section S3.1 for discussion.

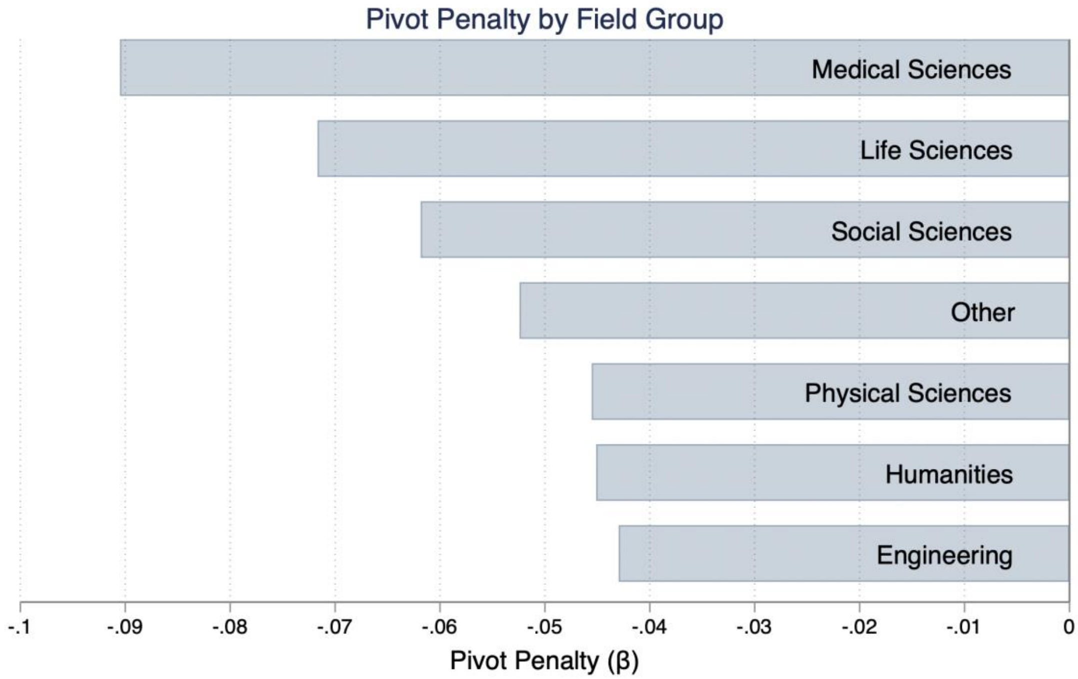

Figure S12: Pivot penalties by field groups. This figure explores heterogeneity in the pivot penalty according to higher level field groupings. Sample includes 40.9 million paper-field pairs published between 1970-2019. Magnitudes vary across field groups, but the pivot penalty appears substantial in diverse areas of study. See Section S3.2 for further discussion.

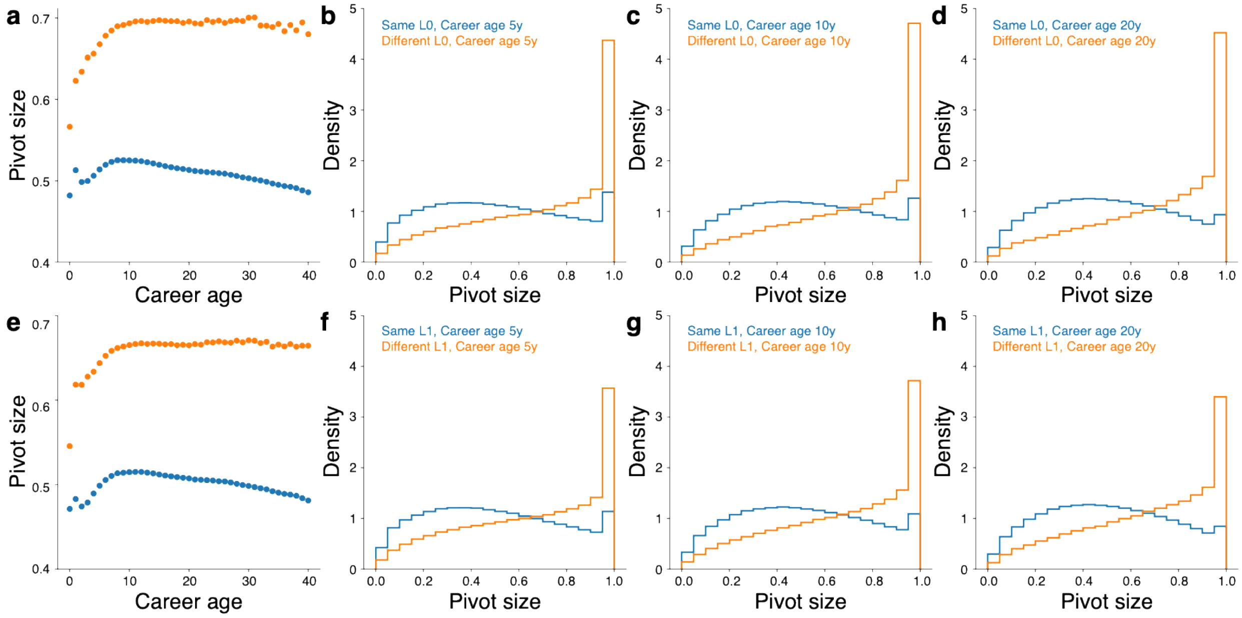

Figure S13: Pivot size and field switching. This figure considers the relationship between pivot size and binary indicators for a change in field. When researchers change field with a new paper, mean pivot sizes tend to be substantially larger, both when switching among the 22 Level-0 fields (**a**, n = 118 million paper-author pairs) or switching among the 154 Level-1 fields (**e**, n = 112 million paper-author pairs). Moreover, the binary measure of field switches is strongly associated with pivot sizes close to 1 (**b-d, f-h**). These findings are broadly similar at different stages of the career. See Section S3.3 for discussion.

S5 Supplementary Information Tables

Panel **a**	Share of L1 fields with negative correlation between pivot size and impact:	Number of fields with at least 20 papers
All 1970-2019 papers	93.5%	153
All 2020 papers	88.2%	149
Non-COVID 2020 papers	89.5%	149
COVID 2020 papers	59.5%	111
Panel b	Share of L1 fields where correlation is becoming more negative over time:	
All 1970-2019 papers	88.2%	153

Table S1: Pivot-impact relationship by scientific field. This table shows that a large majority of fields exhibit negative relationships between pivot size and impact. Further, this relationship is becoming more negative over time. In the 1970-2019 rows, impact is measured as an indicator for being in the 95^{th} percentile of citations by year and field. In the 2020 rows, impact is measured as the journal hit rate, or the probability that a paper will reach the 95^{th} percentile of citations based on journal placement. In all rows, only fields with at least 20 papers are included in the share, with the number of qualifying fields listed for each row. In Panel **a**, the sign of the relationship is estimated within each field using linear regression of impact regressed on pivot size. In Panel **b**, we add to the field-specific regressions an interaction between pivot size and year to estimate the change in slope over time.

Panel **a**	Share of classes with negative correlation between pivot size and impact:	Number of classes with at least 20 patents
All 1980-2015 patents	91.3%	127
Panel **b**	Share of classes where correlation is becoming more negative over time:	
All 1980-2015 patents	76.4%	127

Table S2: Pivot-impact relationship by patent class. This table shows that a large majority of patent classes exhibit negative relationships between pivot size and impact. Further, this relationship is becoming more negative over time. Impact is measured as an indicator for being in the 95th percentile of citations by year and field. In all rows, only classes with at least 20 patents are included in the share, with the number of qualifying fields listed for each row. In Panel **a**, the sign of the relationship is estimated within each field using linear regression of impact regressed on pivot size. In Panel **b**, we add to the field-specific regressions an interaction between pivot size and year to estimate the change in slope over time.

	(1)	(2)	(3)	(4)	(5)
Pivot Size	-0.0687***	-0.0706***	-0.0714***	-0.0688***	-0.0699***
	(0.000774)	(0.00115)	(0.00134)	(0.00186)	(0.00368)
Constant	0.0906***	0.103***	0.109***	0.119***	0.151***
	(0.000463)	(0.000625)	(0.000711)	(0.000939)	(0.00168)
Sample	At least 5 references	At least 15 references	At least 20 references	At least 30 references	At least 50 references
Observations	1,337,008	890,402	737,279	472,913	175,472
R-squared	0.006	0.004	0.004	0.003	0.002

Table S3: The pivot penalty for alternative thresholds for the number of cited references. These analyses use publications in 2010. The dependent variable is an indicator for being in the upper 5th percentile of citations received for the field and publication year. Moving left to right, the columns increasingly restrict the sample, as indicated, according to the number of backwards references a paper makes. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	(1)	(2)	(3)	(4)
Pivot Size	-0.0751***	-0.0414***	-0.0426***	-0.0308***
	(0.000521)	(0.000728)	(0.000788)	(0.000858)
Individual FE		X		
Individual X Field of Journal FE			X	
Individual X Journal FE				X
Observations	3,708,999	3,708,999	3,708,999	3,708,999
R-squared	0.005	0.215	0.299	0.453

Table S4: The pivot penalty with individual, field, and journal fixed effects. This table reports regressions of impact on pivot size. The dependent variable is an indicator for a paper reaching the 95th percentile of citations for the field and year. The regression sample is all papers published between 2005 and 2010 and where an author has multiple papers appear in the same field and journal. Individual fixed effects are added to the model in column 2. Individual by field of journal fixed effects are added in column 3, where the field of each journal is defined by the modal field of papers published in the journal. Individual by journal fixed effects are used in column 4. Comparing columns (4) and (2) we see that the pivot coefficient is 26% smaller net of individual by journal fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

	(1)	(2)	(3)	(4)	(5)	(6)
Pivot Size	-0.0779***	-0.0644***	-0.0530***	-0.0306***	-0.0372***	-0.0500***
	(0.000772)	(0.00124)	(0.00125)	(0.00816)	(0.00874)	(0.0106)
Career Age x Pivot Size		-0.00105***				
		(8.28e-05)				
Career Age		0.00102***				
		(4.76e-05)				
Constant	0.116***	0.102***	0.103***	0.0795***	0.0883***	0.0888***
	(0.000455)	(0.000747)	(0.000685)	(0.00454)	(0.00483)	(0.00575)
Individual Fixed Effects	No	No	Yes	Yes	Yes	Yes
Career Age Sample	All	All	All	10+ years	4-9 years	1-3 years
Observations	1,555,874	1,555,874	1,555,874	29,082	27,554	16,281
R-squared	0.007	0.007	0.369	0.404	0.405	0.412

Table S5: The pivot penalty by career stage. These analyses use publications in 2010. The dependent variable is an indicator for being in the upper 5th percentile of citations received for the field and publication year. Column (1) presents the baseline pivot penalty result with no controls. Column (2) shows a small negative interaction between pivot size and career stage in predicting impact. Researchers further in their career thus face somewhat large pivot penalties, although this steepening of the pivot penalty is small, and much smaller than the general pivot penalty. The regression coefficient of the interaction with career age (-.00105) is 1.6% of the magnitude of the main pivot size coefficient (-.0644). Column (3) presents a baseline specification with individual fixed effects. Columns (4)-(6) then run separate individual fixed effect regressions for the indicated range of career ages, further restricting the sample to authors with exactly the same publication rate over the prior three years (5 publications), to ensure similarity in productivity. These final analyses further show that pivot penalty appears at the earliest stages of the career. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Panel a

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Reduced Form				Two-Stage Least Squares	
	Pivot Size	Hit Paper	Hit Paper (2-yr)	Normalized Citations	Hit Paper	Hit Paper (2-yr)	Normalized Citations
Treated × post	0.025***	-0.004***	-0.007***	-0.041***			
	(0.001)	(0.001)	(0.001)	(0.008)			
Post	-0.017***	0.000	0.001**	0.007	-0.003***	-0.003***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.000)	(0.000)	(0.006)
Pivot size					-0.164***	-0.266***	-1.642***
					(0.024)	(0.024)	(0.313)
YearFE	X	X	X	X	X	X	X
AuthorFE	X	X	X	X	X	X	X
R-squared	0.418	0.153	0.158	0.095	-	-	-
Observations	5,823,683	5,823,683	5,823,683	5,823,683	5,823,683	5,823,683	5,823,683

Panel b

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Reduced Form				Two-Stage Least Squares	
	Pivot Size	Hit Paper	Hit Paper (2-yr)	Normalized Citations	Hit Paper	Hit Paper (2-yr)	Normalized Citations
Treated × post	0.037***	-0.007***	-0.011***	-0.061***			
	(0.001)	(0.001)	(0.001)	(0.015)			
Post	-0.012***	-0.002***	-0.001**	-0.014	-0.004***	-0.005***	-0.033***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)	(0.009)
Pivot size					-0.191***	-0.308***	-1.668***
					(0.035)	(0.036)	(0.411)
YearFE	X	X	X	X	X	X	X
AuthorFE	X	X	X	X	X	X	X
R-squared	0.441	0.159	0.166	0.079	-	-	-
Observations	2,958,536	2,958,536	2,958,536	2,958,536	2,958,536	2,958,536	2,958,536

Table S6: Difference-in-Differences analysis, retractions. This table presents the regression results for Fig. 3 together with alternative specifications. The top table (Panel a) considers the treatment sample defined by having cited a retracted paper at least once prior to its retraction. The bottom table (Panel b) considers the treatment group defined as having cited a retracted paper multiple times prior to its retraction. In both tables the columns are the same. Columns (1) considers the effect of the shock on pivot size. Columns (2)-(4) consider the reduced-form of the shock effect on impact. Impact is measured alternatively as the hit rate of the paper using the whole forward citation window after publication (2), the hit rate of the paper using only the first two years of citations after publication (3), and the citation count of the paper in ratio to the field-year mean (4). Columns (5)-(7) then consider these impact effects again using two-stage least squares. All regressions include individual fixed effects and year fixed effects. Standard errors are clustered at the author level and shown in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Reduced Form			Two-Stage Least Squares		
	Pivot Size	Hit Paper	Hit Paper (2-yr)	Normalized Citations	Hit Paper	Hit Paper (2-yr)	Normalized Citations
Treated × post	0.014***	-0.015**	-0.019***	-0.067**			
	(0.005)	(0.006)	(0.006)	(0.032)			
Pivot size					-1.117*	-1.355**	-4.868
					(0.599)	(0.643)	(2.972)
YearFE	X	X	X	X	X	X	X
AuthorFE	X	X	X	X	X	X	X
R-squared	0.309	0.096	0.086	0.085	-	-	-
Observations	56,257	56,257	56,257	56,257	56,257	56,257	56,257

Table S7: Replication analysis. This table considers replication failures in psychology, where prior work researchers had been building upon is no longer seen as reliable. The table form follows the same structure as Table S6. See also Section S2.7.2 for discussion of methods. All regressions include individual fixed effects and year fixed effects. Standard errors are clustered at the author level and shown in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Field	Number of Papers	Pivot-Impact Regression Estimates		
		Slope	Standard Error	P-value
Distributed Computing	36295	0.012	0.005	0.017
Computer Hardware	15579	0.017	0.007	0.018
Other Information and Computing Sciences	11202	0.025	0.011	0.017
Film, Television and Digital Media	7088	0.018	0.016	0.259
Other Earth Sciences	3015	0.005	0.023	0.826
Visual Arts and Crafts	2195	0.122	0.024	0.000
Art Theory and Criticism	589	0.093	0.085	0.276
Other Law and Legal Studies	140	0.052	0.172	0.763
Other Built Environment and Design	87	0.450	0.187	0.018
Other Philosophy and Religious Studies	73	0.385	0.220	0.085

Table S8: Outlier scientific fields. This table lists the 10 scientific fields that are outliers in showing a positive relationship between pivot size and impact. These 10 fields represent 6.5% of fields and only 0.18% of papers. See Section S3.2 for detailed discussion.

Panel a

	(1)	(2)	(3)	(4)	(5)	(6)
Pivot Size	-0.101***		-0.0978***	-0.104***		-0.0987***
	(0.00172)		(0.00175)	(0.00276)		(0.00278)
Conventionality (median)		0.000143***	1.76e-05		0.000130***	-4.82e-06
		(1.22e-05)	(1.24e-05)		(5.01e-05)	(5.00e-05)
Novelty (tail)		-0.00118***	-0.000971***		-0.00137***	-0.00115***
		(3.26e-05)	(3.27e-05)		(5.66e-05)	(5.67e-05)
Field FE	Y	Y	Y	Y	Y	Y
Conventionality Range	.25 to .75 percentile	.25 to .75 percentile	.25 to .75 percentile	.40 to .60 percentile	.40 to .60 percentile	.40 to .60 percentile
Observations	379,346	379,346	379,346	151,646	151,646	151,646
R-squared	0.012	0.006	0.014	0.013	0.008	0.016

Panel b

	(1)	(2)	(3)	(4)
Pivot Size	-0.108***	-0.102***	-0.106***	-0.101***
	(0.00391)	(0.00393)	(0.00872)	(0.00876)
Conventionality (median)		9.46e-05		0.000568
		(0.000141)		(0.00155)
Novelty (tail)		-0.00112***		-0.000980***
		(8.18e-05)		(0.000181)
Field FE	Y	Y	Y	Y
Conventionality Range	.45 to .55 percentile	.45 to .55 percentile	.49 to .51 percentile	.49 to .51 percentile
Observations	75,868	75,868	15,212	15,212
R-squared	0.015	0.017	0.018	0.020

Table S9: Pivots and combinations. This table presents regression evidence considering pivoting behavior, novel combinations, and conventional combinations together. The dependent variable is an indicator for being a high impact paper, defined as in the upper 5th percentile of citations received for the field and year. The analysis uses papers published in 2010. See Section S2.3 for details on the combinatorial measures. To test whether pivot size predicts citation impact net of conventionality and novelty, we control for all three variables independently and over narrow ranges of the conventionality score. In Panel **a**, the first three columns consider the middle 50 percent of observations by conventionality, while the second three columns consider the middle 20 percent of observations by conventionality. In Panel **b**, the first two columns consider the middle 10 percent of observations by conventionality, while the next two columns consider the middle 2 percent of observations by conventionality. These regressions continue to show a substantial impact penalty. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Author	Year	Pivot Size	Paper Title
1	**2020**	**0.95**	**The challenges of modeling and forecasting the spread of COVID-19**
	2019		Reducing Bias in Estimates for the Law of Crime Concentration
	2018		Sequential data assimilation for 1D self-exciting processes with application to urban crime data
	2018		The Role of Graphlets in Viral Processes on Networks
2	**2020**	**0.51**	**A SARS-CoV-2 vaccine candidate would likely match all currently circulating variants**
	2019		Humoral Response to the HIV-1 Envelope V2 Region in a Thai Early Acute Infection Cohort
	2019		Prolonged evolution of the memory B cell response induced by a replicating adenovirus-influenza H5 vaccine
	2019		Mosaic nanoparticle display of diverse influenza virus hemagglutinins elicits broad B cell responses
3	**2020**	**0.18**	**Enhanced isolation of SARS-CoV-2 by TMPRSS2-expressing cells**
	2019		Middle East Respiratory Syndrome Coronavirus in Dromedaries in Ethiopia Is Antigenically Different From the Middle East Isolate EMC
	2019		Generation of bat-derived influenza viruses and their reassortants
	2017		Characterization of a Novel Bat Adenovirus Isolated from Straw-Colored Fruit Bat (Eidolon helvum)

Table S10: Researcher pivot examples. This table presents examples for three researchers with substantially different pivot sizes. To see pivot size variation in a common context, we examine researchers who published a 2020 paper related to COVID-19. We present the paper title for the focal paper as well as papers titles for three recent works prior to 2020. The high-pivot researcher (top) makes a large jump from unrelated topics. The middle-pivot researcher is moving from study of other viruses to the coronavirus. And the low-pivot researcher has prior work on the coronavirus.

References

1 Dimensions, R. *Dimensions COVID-19 publications, datasets and clinical trials*. (2020).
2 Herzog, C., Hook, D. & Konkiel, S. Dimensions: Bringing down barriers between scientometricians and data. *Quantitative Science Studies* **1**, 387-395 (2020).
3 Visser, M., van Eck, N. J. & Waltman, L. Large-scale comparison of bibliographic data sources: Scopus, Web of Science, Dimensions, Crossref, and Microsoft Academic. *Quantitative Science Studies* **2**, 20-41 (2021).
4 Hendricks, G., Lammey, R., Ofiesh, L., Bilder, G. & Pentz, E. *Crossref and Retraction Watch*, <https://www.crossref.org/blog/news-crossref-and-retraction-watch/> (2023).
5 Collaboration, O. S. & others. Estimating the reproducibility of psychological science. *Science* **349**, aac4716 (2015).
6 Yin, Y., Gao, J., Jones, B. F. & Wang, D. Coevolution of policy and science during the pandemic. *Science* **371**, 128-130 (2021).
7 Kogan, L., Papanikolaou, D., Seru, A. & Stoffman, N. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* **132**, 665-712 (2017).
8 Radicchi, F., Fortunato, S. & Castellano, C. Universality of citation distributions: Toward an objective measure of scientific impact. *Proceedings of the National Academy of Sciences* **105**, 17268-17272 (2008).
9 Vinkler, P. *The evaluation of research by scientometric indicators*. (Elsevier, 2010).
10 Marx, M. & Fuegi, A. Reliance on science: Worldwide front‐page patent citations to scientific articles. *Strategic Management Journal* **41**, 1572-1594 (2020).
11 Ahmadpoor, M. & Jones, B. F. The dual frontier: Patented inventions and prior scientific advance. *Science* **357**, 583-587 (2017).
12 Uzzi, B., Mukherjee, S., Stringer, M. & Jones, B. Atypical combinations and scientific impact. *Science* **342**, 468-472 (2013).
13 Lin, Z., Yin, Y., Liu, L. & Wang, D. SciSciNet: A large-scale open data lake for the science of science research. *Under review* (2022).
14 Starr, E. & Goldfarb, B. Binned scatterplots: A simple tool to make research easier and better. *Strategic Management Journal* **41**, 2261-2274 (2020).
15 Correia, S. reghdfe: Stata module for linear and instrumental-variable/GMM regression absorbing multiple levels of fixed effects. *Statistical Software Components s457874, Boston College Department of Economics* (2017).
16 Collaboration, O. S. Estimating the reproducibility of psychological science. *Science* **349**, aac4716 (2015).
17 Bornmann, L. Field classification of publications in Dimensions: A first case study testing its reliability and validity. *Scientometrics* **117**, 637-640 (2018).
18 Herzog, C. & Lunn, B. K. Response to the letter ‘Field classification of publications in Dimensions: a first case study testing its reliability and validity’. *Scientometrics* **117**, 641-645 (2018).