Adaptability and the Pivot Penalty in Science and Technology

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

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

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

[3]Northwestern Institute on Complex Systems, Northwestern University, Evanston IL

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

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

[6]Department of Economics, University of California – Berkeley, Berkeley CA

[7]National Bureau of Economic Research, Cambridge MA

[¶]These authors contributed equally to this work.

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

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Abstract

Scientists and inventors set the direction of their work amidst an evolving landscape of questions, opportunities, and challenges. This paper introduces a measurement framework to quantify how far researchers move from their existing research when producing new works. We apply this framework to millions of scientific publications and patents and uncover a pervasive "pivot penalty," where the impact of new research steeply declines the further a researcher moves from their prior work. While conceptual frameworks often emphasize novel perspectives and outsider advantages in driving scientific and technological progress, we find that the pivot penalty applies nearly universally across the sciences, and in patenting, and has been growing in magnitude over the past five decades. The rising penalty is consistent with increasingly narrow specializations of researchers with time, and when researchers undertake large pivots, a signature of their work is weak engagement with established mixtures of prior knowledge. Investigating COVID-19 research as a high-scale case study, we see widespread engagement with the pandemic, yet the pivot penalty remains severe. 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. The results have implications for individual researchers, research organizations, science policy, and the capacity of science and society as a whole to confront emergent demands.

Science has been described as an endless frontier [1-4], engaging an evolving array of questions, opportunities, and challenges [5, 6]. New areas 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 engage emergent opportunities and demands [7-10]. Adaptability to threats and opportunities is thus critical to scientific and technological progress [1-3], and adaptive success or failure can underpin the relative progress or collapse of organizations, economic regions, and societies [1-4, 11, 12].

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 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. The specialization of expertise [13], the design of funding systems [14, 15], and the nature of research incentives, culture, and communities [16-19] may all limit the capacity of a given individual to respond effectively to changing opportunities and demands [20-23]. On the other hand, the value of novelty [24-26] and exploration [27-29] in creative search suggests that reaching further from one's usual research area might be especially fruitful [30, 31], and new entrants or "outsiders" to a given area are sometimes thought to be especially capable of transformative ideas [19, 32]. And collaborations may further help to overcome individual limits and facilitate fruitful entry to new areas [13, 33-38]. Indeed, a researcher who continues to exploit an existing direction may face diminishing returns while missing the opportunities afforded in other areas [27, 39]. By contrast, 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, leveraging high-scale data to examine outcomes when researchers engage 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. First, we examine pivots across science and technology, studying scientific articles indexed by Dimensions from 1970-2020 and U.S. patents granted from 1975-2020 (see SM 1.1-2). We further focus on scientists and inventors with at least 5 papers or patents, respectively, over their career, which allows us to measure how a person's research shifts across their works (see SM 2.1). For these scientists and inventors, our focal analyses consider 37 million scientific articles indexed by Dimensions and 1.8 million U.S. patents. Second, we study the COVID-19 pandemic, which created a major shift in research demands across the scientific enterprise. Here we identify COVID-19 related scientific articles using keyword searches [40, 41] of titles and abstracts, yielding 95,511 COVID-19 articles in 2020, which include both peer-reviewed publications and preprints. See SM for further data details.

To quantify pivots for researchers, we calculate a cosine-similarity metric (Fig. 1A) that measures the extent to which a given new work departs from a researcher's prior body of work. 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. The pivot measure, Φ_i^j, is then defined as 1 minus the cosine of these two vectors:

$$\Phi_i^j = 1 - \frac{R_i^j \cdot R_i}{\left\|R_i^j\right\| \|R_i\|} \qquad (1)$$

The measure Φ_i^j thus 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 entirely on a novel set of journals. 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 SM and Fig. S1). In the patent context, where journal information is not available, we use technological field codes to measure pivots. 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), and we further examine all possible classification levels in the supplementary material.

Fig. 1 shows the distribution of pivoting behavior using this measurement framework and 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). Anticipating our case study of COVID-19 research, we observe a sharp difference in pivot size comparing COVID-19 and non-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). Full pivots ($\Phi_i^j = 1$) appear 1.83 times more often among COVID-19 authors (p<.0001).

The highly variable nature of the pivot size is especially prominent in patenting, where we observe a bimodal distribution (Fig. 1C) with weight at both extremes, showing a tendency for both very small pivots and large jumps. Given the hierarchical nature of the patent technology codes, we can further examine pivoting from the broadest level-1 classification level (9 sections) to the most detailed level-5 classification (210,347 subgroups). Not surprisingly, the pivot distribution for inventors shifts leftward when using broader technology categories (Fig. S2). In other words, inventors pivot less from their broadest technology areas (the section or section-class level) and pivot much more among the narrowest classifications (the section-class-subclass-group-subgroup level). Yet, regardless of the technology categories we use, the pivot behavior of inventors remains widely dispersed.

As scientists and inventors shift from their earlier research, a central question is how impactful their work becomes. We consider 37 million papers published from 1970 to 2020 across 154 fields. To quantify impact, we calculate the paper-level hit rate, a binary indicator for whether a given work was in the upper 5% of citations received within its field and publication year [33]. Fig. 2A reveals a striking fact: looking at all of sciences, larger pivots are systematically associated with lower impact. Indeed, we observe a large and 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. For patents, we 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. 2B). 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 appears robustly when we measure inventor pivots at any technology-classification level, from the broadest to the narrowest (Fig. S3).

Quantifying this “pivot penalty” over time, we find the relationship between pivot size and impact in science has become increasingly negative over the past five decades (Fig. 2C). Furthermore, these findings generalize widely not just across time but also across scientific fields. Studying separately each of the 154 subfields, we find that 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. 2D). Studying separately 127 level-2 technology classes, we find that 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. S4).

In examining the outcomes of pivots, one can also look beyond citation impact. For papers, we further measure whether a paper is referenced in a future patent [3, 42], 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. S5). 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 [43]. We see that the market value of a patented invention declines steeply with pivot size, with the market value declining 29% comparing the highest-pivot to the lowest-pivot patents (Fig. S6). These findings indicate that the pivot penalty also appears when considering practical use and market value, and beyond the citation behavior within a community of researchers.

Altogether, we observe striking empirical regularities that generalize across science and technology. Indeed, despite the distinct nature of journal 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 impact penalties, and increasingly so with time.

The growing impact advantage to narrowness in ambit of research is consistent with researchers becoming increasingly specialized as scientific and technological knowledge deepens [13, 42]. It indicates substantial difficulties for researchers in entering new areas and heightens the concern in innovation communities that research with wide reach or novel orientations is challenging [10, 43-45]. To further unpack the nature of the pivot penalty, we next examine the pivot penalty in view of both reputational perspectives and creativity frameworks.

An established reputation in a local research community may provide impact advantages within that community and a relative disadvantage outside it [44], suggesting that we further examine the pivot penalty in light of reputational considerations. To this end, we examine what happens when a given researcher publishes multiple papers in the same year and in the same field, and even in the same exact journal (Table S3), allowing us to further examine pivots when the author's work appears before a relatively consistent audience. We find that while the pivot penalty is approximately 28% less steep when an individual is publishing in the same journal, an attenuation that is consistent with reputational forces, the vast majority of the relationship remains. Indeed, the pivot penalty appears extremely strong even when publishing before a consistent audience and at a consistent moment in the researcher's career. Together with the findings for market value (Fig. S6) and practical applications of science (Fig. S5), the pivot penalty appears both within a scholar's research community and in the substantive use and valuation of ideas by distant communities.

Turning to creativity perspectives, a canonical framework emphasizes an "explore vs. exploit" tradeoff, where exploitation involves relatively low-risk innovative attempts within one's current research stream, while exploration involves a high-risk but potentially higher-return departure into more distant areas [27, 32, 39]. Our analyses have looked at upper-tail outcomes, but it is possible that the value of large pivots lies in even rarer and more extreme positive outcomes. Surprisingly, however, we find that high-pivot research receives lower citations across the entire citation distribution (Fig. S7A). In the very upper tail, such as in the upper 1% or upper 0.1% of citation impact, high-pivot work is even more heavily dominated by low-pivot work (Fig. S7B). Rather than suggesting a tradeoff between risk and reward, these findings suggest instead a more fundamental difficulty of venturing into new areas.

Canonical creativity frameworks further emphasize that new works can be seen as new combinations of existing material [45-47], providing an additional lens to probe the pivot penalty. Indeed, prior literature has shown that high-impact research tends to have two key combinatorial characteristics that operate simultaneously [24, 48]. First, high-impact work is primarily grounded in highly conventional mixtures of prior knowledge. Second, amidst this heavy orientation on conventional foundations, high-impact work simultaneously injects a small dose of atypical combinations that are unusual in science. Following this literature, we further measure the novelty and conventionality of combinations in a given paper and relate these measures to pivot size (see SM S2.3 for methods). We find that high-pivot work is associated with a higher degree of atypical combinations (Fig. S8A). In other words, when a researcher pivots, the researcher not only does something new personally but also tends to introduce novel combinations of knowledge in science. Yet, at the same time, high-pivot papers show distinctly low conventionality (Fig. S8B), locating a key characteristic that the exploratory work of individuals 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, providing descriptive insight into the nature of the pivot penalty.

The pivot penalty appears as a fundamental regularity, with creative signatures that point to the challenge of exploring new areas. It also raises questions about whether there are research contexts where researchers might pivot relatively successfully. One key question is whether an important new research area in science can offset the penalty, and how scientists respond. To further understand pivoting behavior, we next turn to a consequential case study: the COVID-19 pandemic, which offers a unique opportunity to examine how scientists engage important, emergent research questions. Indeed, confronted by COVID-19, the world has 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 exactly zero were studying COVID-

19 specifically—the advent of COVID-19 called upon researchers across the frontiers of knowledge to consider a shift in their work [49-51] to address new and high-demand research questions.

Figure 3 investigates COVID-19 research and shows that pivoting to address COVID-19 was widespread. Although the earliest papers on COVID-19 did not appear until January 2020 [52, 53], by May 4.5% of all new scientific papers were related to COVID-19 (Fig. 3A). Further, while fields differed in their rate of pivoting, all fields pivoted to COVID-19 related research (Fig. 3B). Medical and health sciences exhibit the greatest COVID-19 orientations, while social science fields – including economics, education, and law – also engaged COVID-19 relatively heavily, speaking to the pandemic's socioeconomic challenges [40, 41]. The ubiquitous yet heterogeneous shift to COVID-19 is also pronounced at higher field specificity (Fig. S9). Furthermore, while fields inherently differ in their propensities to produce COVID-19 research (Figs. 3D, S9), we find that scientists in every field undertake unusually large pivots when writing COVID-19 related papers. In all 154 subfields, mean pivot sizes for COVID-19 papers are larger than for non-COVID papers (Fig. 3D). Fig. 3C 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, where control authors are matched to the COVID authors by cohort, field, and publication rate (see SM for details). We find that the average pivot size presents a broadly stable pattern over time yet features a clear jump for COVID-related work in 2020, 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 engage COVID-19.

We next turn to impact. Given that 2020 papers have had relatively little chance to receive citations [54], we examine journal placement, where each journal is assigned the historical hit rate of its publications within its field and year (see SM S2.2). Fig. 3E considers all papers published in 2020, separating them into COVID and non-COVID (red vs blue lines). 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. At the same time, the negative relationship between pivoting and impact appears in both groups and is steep for COVID research.

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. Further, the COVID impact premium is mostly offset by the unusually large pivots associated with COVID research. Indeed, the upper 45% of COVID-19 papers by pivot size have lower average journal placement than papers with median or below pivot size among non-COVID work. We see a similar surge in interest, and penalty for high pivots, using citations to the specific papers (Fig. S10).

Overall, COVID-related work presents two extremely strong yet sharply 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 unearth a central tension for individual researchers and the adaptability of science: while engaging a high-demand area has value, pivoting exhibits offsetting penalties. The SM examines this tradeoff further net of individual scientist fixed effects, which account for a specific scientist's impact and pivot tendencies and shows that this fundamental tradeoff is robust when comparing within a given researcher's papers (Fig. S11). Thus, even though a high-demand area like COVID-19 offers an impact premium, within a given individual, low-pivot work is more likely to outperform higher-pivot work by that individual.

The pivot penalty presents a striking challenge in shifting research streams, raising the question of potential moderating factors that might facilitate successful pivots. We close by studying three key possibilities, informed by the science of science literature [55-57], and investigate further the sciences as a whole and the COVID-19 case study. First, what is the relationship between an individual's productivity level and career stage in pivoting? Second, what role may teamwork play in facilitating pivots? Third, what role does funding play? Finally, can any of these features overcome the pivot penalty seen above?

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]. Surprisingly, however, we find that older scientists were disproportionately more likely to pivot into COVID research (Fig. 4A), a result that holds for a large majority of fields (Fig. S12A-B), and the pivot penalty appears among both older and younger researchers (Fig. 4B). Similarly, highly productive scholars proved far more likely to engage COVID-19 work (Fig. 4A), but both higher and lower impact scholars experience the pivot penalty, in science in general and within COVID-19 research (Fig. 4C). Thus, while creative orientation, skills, and other resources or capabilities may vary according to a researcher's productivity or career stage [17, 19, 58], the pivot penalty appears persistently within different career stages or productivity levels.

Teamwork may also be a critical feature in facilitating adaptability. Not only are teams increasingly responsible for producing high-impact and novel research [24, 29, 33, 35], they can also aggregate individual expertise [13], extending an individual's reach and promoting subject-matter flexibility [25, 59]. We find that team size has indeed been 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. S12C). Further, COVID-19 authors work to an unusual degree with new coauthors (Fig. 4D), rather than existing collaborators, and engaging new coauthors is associated with larger pivots (Fig. S13A-B). These results are consistent with teamwork expanding reach [13, 36, 37]. Nonetheless, we again see the pivot penalty in both large and small teams, and in teams with and without new coauthors (Fig. 4E-F). Thus, while bigger teams and teams with novel coauthors appear to predict higher impact, the pivot penalty persists.

Finally, we 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. 4G). 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. 4H).

Together, Fig. 4 presents key features that condition pivoting, including an individual's career stage and productivity, 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 all these features together (see SM S2.5), finding that net of all these features, the pivot penalty remains substantial in magnitude (Fig. 4I).

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 both individual researchers, research organizations, and science and society as a whole. At an individual level, a researcher must regularly 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 [19, 24-32], suggesting a risk vs reward tradeoff as researchers venture further from their prior expertise. However, as Einstein once 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…" [60]. Consistent with Einstein's observation, we find that researchers face systematic challenges to pivoting research, and increasingly so with time. This 'pivot penalty' applies to both science and technology, generalizes across research subfields, and extends to the practical use and market value of ideas, external to the research domain. In the COVID-19 pandemic, the enormous demand for COVID-related research attracts numerous researchers and provides them an impact premium; yet we find that the pivot penalty continues to appear strongly among scholars who reached further to engage COVID research.

The pivot penalty, and its steepening with time, raise key questions for research organizations and research policy. For example, businesses and other organizations are often displaced by new entrants [61, 62], despite R&D efforts by the incumbents, which often fail to understand or embrace new technological opportunities [27, 39, 63]. The pivot penalty, uncovered in this paper, reinforces this organizational 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 [64, 65].

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 [66], but the pivot penalty suggests that, unlike typical investments, adjustments to the science portfolio are governed by substantial inertia [67]. 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 [19, 68] 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 applies to high-demand areas like 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? Understanding such sequential dynamics may reveal further insight about the nature of creative search [26-27, 31] with implications for organizational incentives and tolerances for failure. Lastly, pivoting to engage 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 [9, 63, 69-72], suggesting the uncovered pivot penalty may be a generic property of many social and economic systems, with potential applicability in broader domains.

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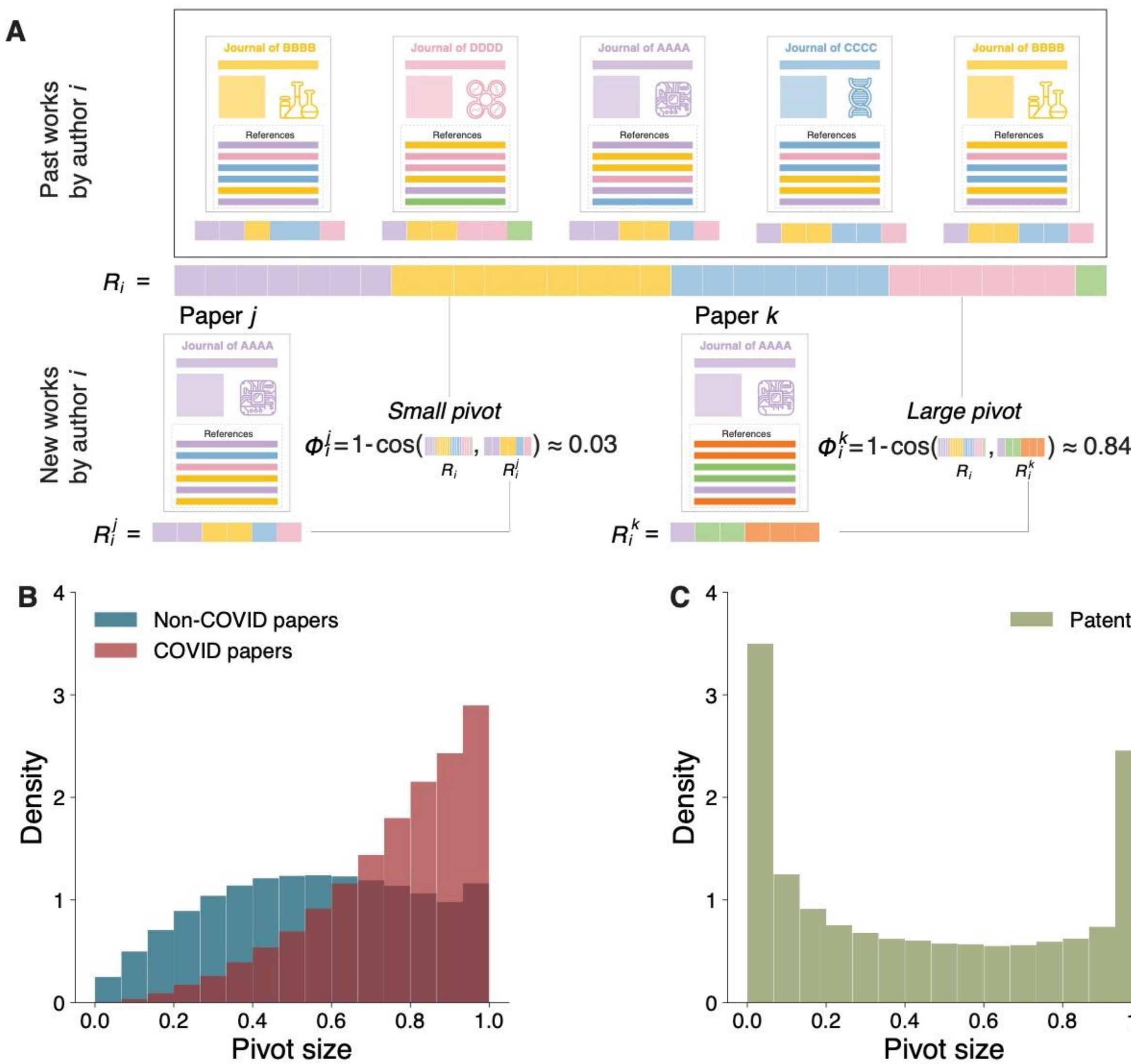

Figure 1. Quantifying Research Pivots. (**A**) The pivot measure compares a focal work against prior works by the same researcher. An increasing value on the [0,1] interval indicates a larger pivot from the researcher's prior work. In the sciences, journals are used to define research areas (pictured); 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.

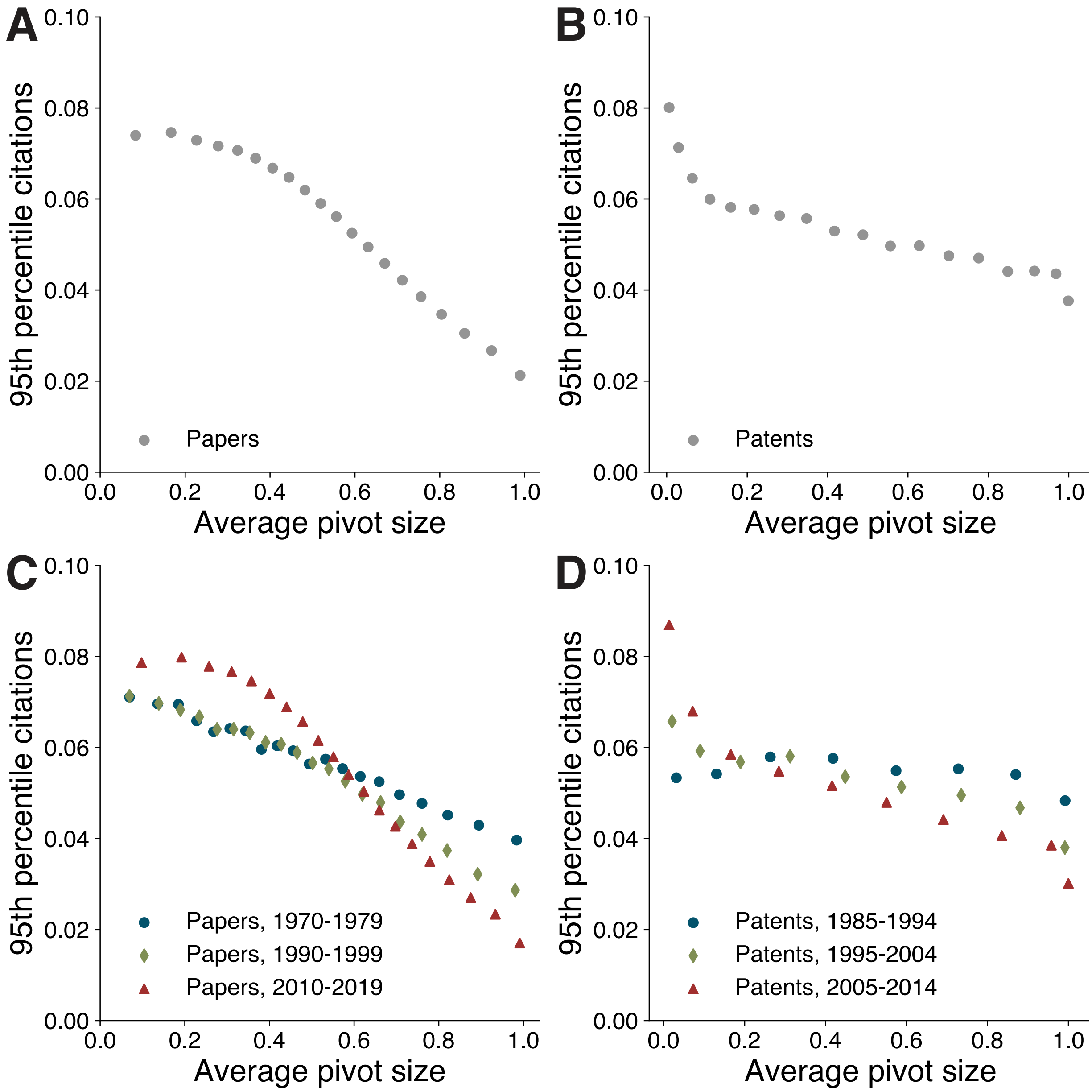

Figure 2. The Pivot Penalty. (**A**) The probability of being a hit paper is a decreasing function of pivot size. This panel includes 37 million papers published from 1970-2019. (**B**) The probability of being a hit patent is also a decreasing function of pivot size. This panel includes 1.8 million U.S. patents granted from 1980-2015. (**C-D**) The pivot penalty is increasingly steep with time. In recent decades, larger pivots appear increasingly low impact in science (**C**) and a steepening pivot penalty also appears in patenting (**D**).

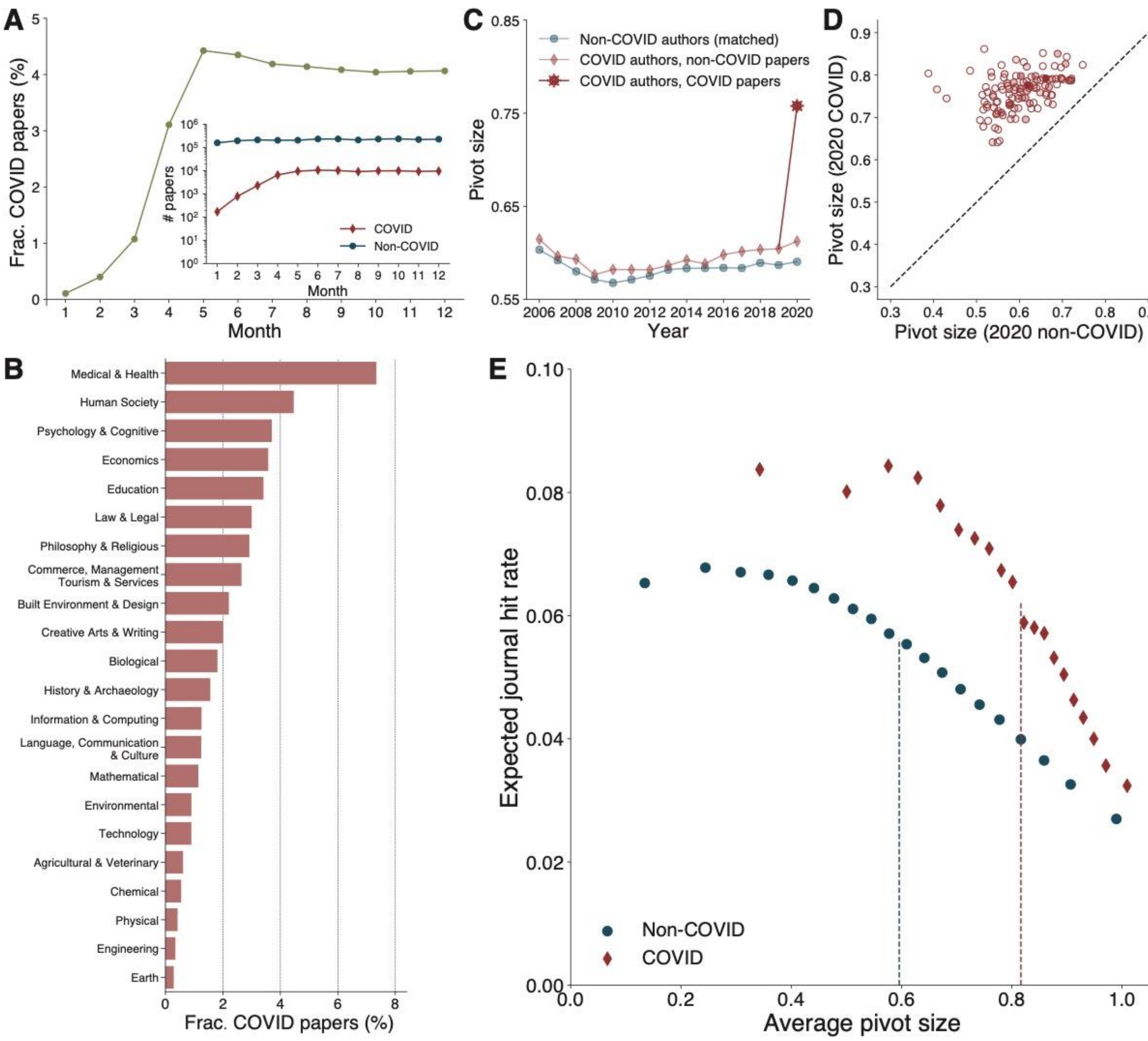

Figure 3. Scientific Pivots and COVID-19. (**A**) Science rapidly shifted to COVID-19 research in 2020, with COVID-19 publications rising to 4.5% of all science publications in May 2020 and maintaining similarly high rates thereafter. (**B**) While health sciences and social sciences featured the strongest 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.

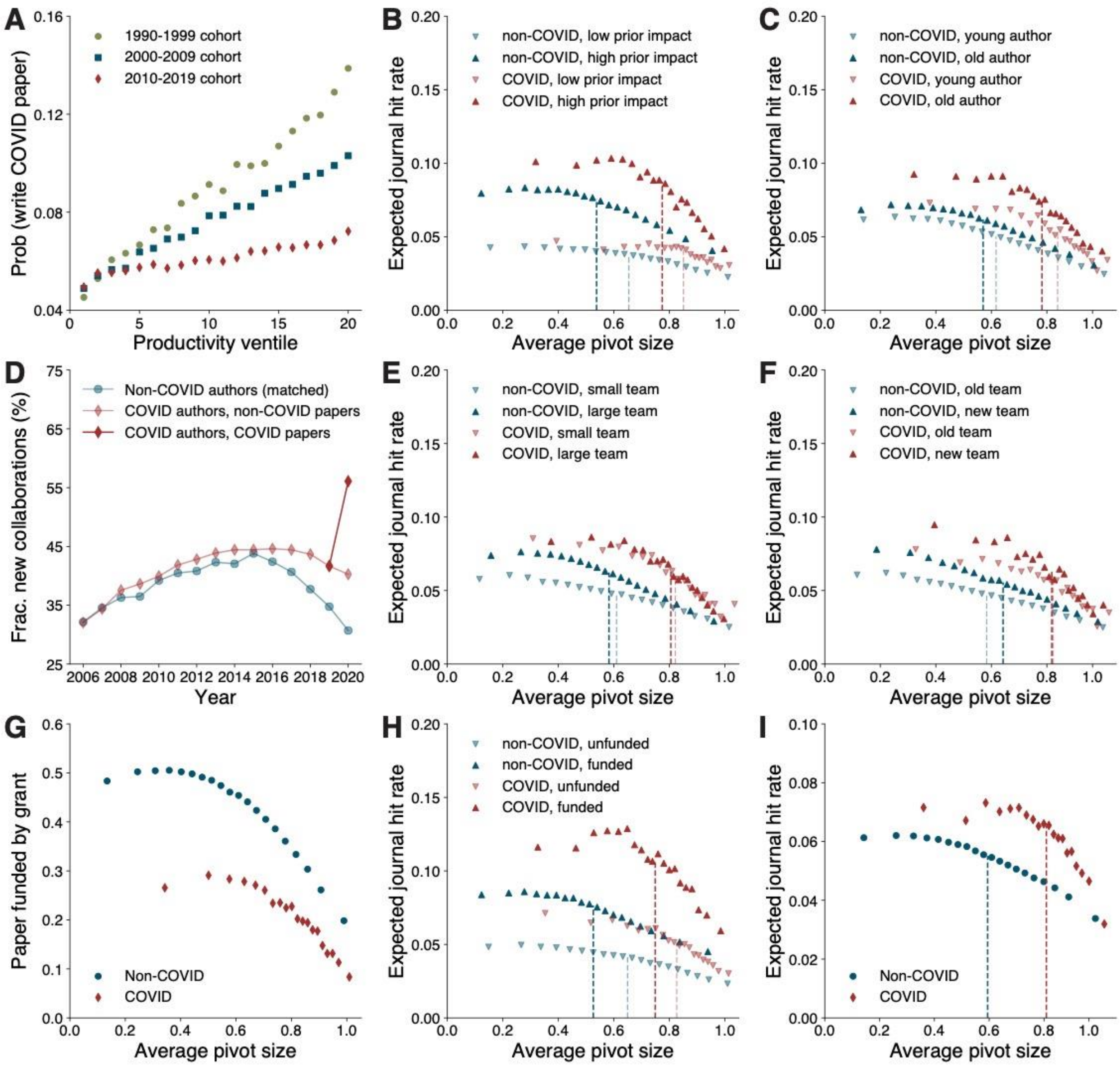

Figure 4. Further Features Condition Adaptability but the Pivot Penalty Persists. (**A**) We group scientists based on their first publication year and their prior productivity among their cohort. Higher productivity and older scientists are substantially more likely than younger scientists to pivot into COVID-19 research. Yet the pivot penalty endures for different productivity levels (**B**) and career stages (**C**). (**D**) 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 (**E**) and when engaging new or existing coauthors (**F**). (**G**) 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 (**H**). (**I**) 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. See SM S2.5 for details.

Supplementary Information for
Adaptability and the Pivot Penalty in Science and Technology

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

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

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

[3]Northwestern Institute on Complex Systems, Northwestern University, Evanston IL

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

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

[6]Department of Economics, University of California – Berkeley, Berkeley CA

[7]National Bureau of Economic Research, Cambridge MA

[¶]These authors contributed equally to this work.

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

S1 Data description

S1.1 Dimensions publication 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. Publication data are updated on a daily basis, allowing us to collect reference information in a timely manner. Here we collected all publications added to Dimensions database before December 31, 2020 (116 million papers in total). 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 restrict our analysis to the 45.2 million papers with at least five references. 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 shows that many are commentary or editorial pieces that cite very few references, while some others are due to the lack of reference data sharing between Dimensions and some publishers. Nevertheless, 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 references 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).

COVID-19 related publications We constructed a set of COVID-19 related publications using a keyword search method and following previous work[4] 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 95.5K COVID-related papers.

Author name disambiguation and affiliation disambiguation One important yet challenging 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. Dimensions has also mapped raw affiliation strings to GRID whenever possible, offering unique affiliation IDs to 75.1% of records in the data. In sections of our analysis that use author-level data, such as pivot size and new collaborators, the analysis is restricted to papers with at least one disambiguated author.

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. For all other uses of field effects, including calculating citation percentiles or using field fixed effects in a regression, we group papers based on their distinct combination of fields.

S1.2 USPTO patents data

We further leverage data of 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 ever 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 that have not been withdrawn. 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 Patent Examination Research Dataset (PatEx). We then remove all patents that are associated with at least one "parent" patent in continuation records. Together, we are left with 6.27 million records after filtering. Consistent with our selection on publication data (S1.1), we focus on patents with at least 5 patent references, resulting in a subset of 3.74 million patents in total.

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 rely on this information to construct inventor career trajectories.

Technology class 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 Fig. 1 and 2 are 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. For calculation of hit patents, we use the primary class-level information of each patent.

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.

For part of the funding analysis, we focus our attention on two major funding organizations in the United States: The National Science Foundation (NSF) and the National Institutes of Health (NIH). We look broadly at all papers and individuals funded by the NSF and NIH, as well as the papers and authors specifically funded by these organizations for COVID-19 research. One technical challenge here is that COVID-related grants may not be directly searchable following the approach in S1.1, as funders like the NIH distributed a large amount of COVID grant money as supplementary funding to existing projects, even if the original project does not appear directly related to COVID. To this end, we acquire the list of COVID grants from official reporting systems of NIH and NSF, i.e. querying NIH grants marked as "NIH COVID-19 Response" from NIH RePORTER and searching for "COVID" in NSF RAPID awards. We remove grants with starting date earlier than 2020 and link the rest to Dimensions grant data using internal grant numbers, yielding 1,375 NIH projects and 1,054 NSF projects.

S2 Methods

S2.1 Individual careers

In analyses where we compare authors' 2020 papers to their prior research, we focus on a subsample of "established" authors that have at least 5 publications by the end of 2019. Among the 4.4 million disambiguated authors that published at least one research article in 2020, 2.1 million of them are in the established author subset, having at least 5 prior publications. We collect all past publications of the established authors and calculate their first and last years of publication, major field of research (the modal level-0 and level-1 field of their publications), and total number of publications in the 5 years leading up to 2020 (2015-2019). To calculate pivot size for each established author, we compare the references on their 2020 papers to papers published in the previous three years (the measure featured in the main text) as well as over their complete publication history (as a robustness test examined below). We also use the established author subset for analysis of new co-authors as described in Section S2.4. Similarly, we also focus on a subsample of "established" inventors that have at least 5 patents in our patent data analysis.

S2.2 Impact 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. We additionally measure impact in 2020 using journal placement rather than citations because of the limited time for citations to accrue to recently published papers. For the journal impact measure, we mirror the 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. 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 articles published in the same year with the same primary class.

S2.3 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[5]. 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 10th percentile z-score is below 0, and we denote a "high median conventionality" paper if its

50th percentile z-score is in the upper half of all papers[5]. 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 areas but sprinkles in new combinations of existing knowledge as well[5]. In this paper, we build on a pre-calculated version of novelty and conventionality provided by SciSciNet, an open source database[6].

S2.4 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 established 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. We focus only on established authors in order to measure interactions between authors with independent research portfolios, rather than new graduate students or post-docs without a research track-record.

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. For this analysis, we require the focal author and the collaborator to have at least 5 previous publications. 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 coming 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.

S2.5 Regression methods

To examine relationships between two variables (Fig. 2, Fig. 3E and Fig. 4B-C,E-I), we use a binned scatterplot[7] to show correlations. The advantage of a binned scatterplot is to present statistical relationships without imposing a linear or other functional form on the data. 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, the set of papers from each decade are separately binned into 20 groups according to average pivot size and the mean citation hit rate is plotted for each bin.

In specific cases (Fig. 3E, 4G, and 4I), we use regression methods to present the binned scatterplot net of control variables. For example, in Fig. 3E, we are interested in the relationship between pivot size and impact, holding the scientific field fixed. To implement this analysis, we residualize both our pivot size and impact measure (95th percentile citations) as follows[8,9]. We first estimate the following OLS models:

$$\text{PivotSize}_i = \alpha_1 + \mathbf{F}_i'\theta_1 + \varepsilon_{1i}$$

$$\text{Impact}_i = \alpha_2 + \mathbf{F}_i'\theta_2 + \varepsilon_{2i}$$

where **F** is a vector of L1 field fixed effects and ε_1 and ε_2 are idiosyncratic error terms. We use the estimated parameter values $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\theta}_1$, and $\hat{\theta}_2$ to residualize our pivot size and impact measures:

$$\widetilde{\text{PivotSize}}_i = \text{PivotSize}_i - \hat{\alpha}_1 - \mathbf{F}_i'\hat{\theta}_1$$

$$\widetilde{\text{Impact}}_i = \text{Impact}_i - \hat{\alpha}_2 - \mathbf{F}_i'\hat{\theta}_2.$$

We then apply the binned scatterplot technique to the residualized data (adding back the mean values of pivot size and impact to properly scale the plots). In Fig. 3E, we perform this residualization separately for COVID papers and non-COVID papers and plot the resulting relationships on the same axes. In Fig. 4G, we replace the impact measure as the dependent variable with a binary indicator for whether the paper acknowledges a grant.

For the wide-ranging multivariate regression results presented in Fig. 4I and Fig. S11, we follow the same residualization procedure, but include additional controls to the **F** vector. 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. S11, we include individual fixed effects, or in other words control for all fixed characteristics associated with each author id.

In Fig. 4B-C, E, and F, we split the COVID and non-COVID samples into groups based on the median prior impact, career age, team size, and number of new collaborators. In Fig. 4H we split the sample based on whether the paper was connected to a funding source. The four series in each plot follow the same residualization approach used in Fig. 3E, again controlling for field fixed effects.

S2.6 Matched Authors

In Figs. 3C and 4D, 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 established 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 also with 6,406 authors.

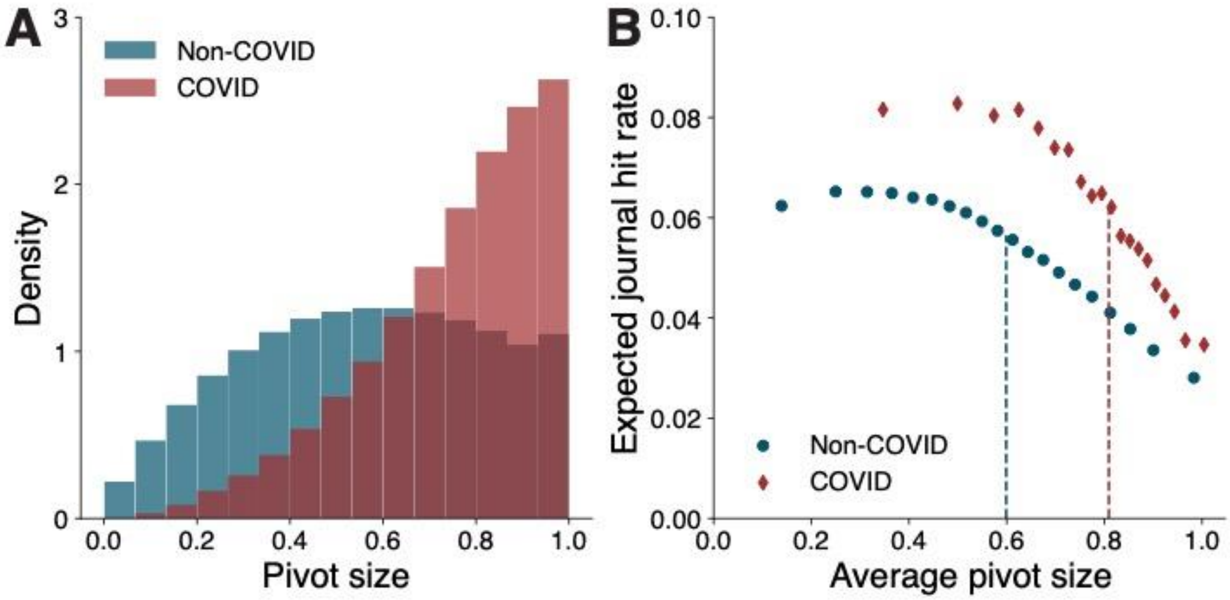

Figure S1: Quantifying pivot size using an author's full publication record. In the main text, we measure pivot size comparing the author's focal paper with that author's prior three years of work. Here we examine pivot size using the entire history of that author's work. **(A)** The large shift in pivot size for COVID papers is evident when pivot size is measured by comparing 2020 papers to all past work. This shift is comparable to Fig. 1B, where pivot size is measured using only papers published in the prior 3 years. **(B)** The negative relationship between pivot size and impact is similar in slope when using the full career pivot metric here or the 3-year metric as shown in Fig. 3E.

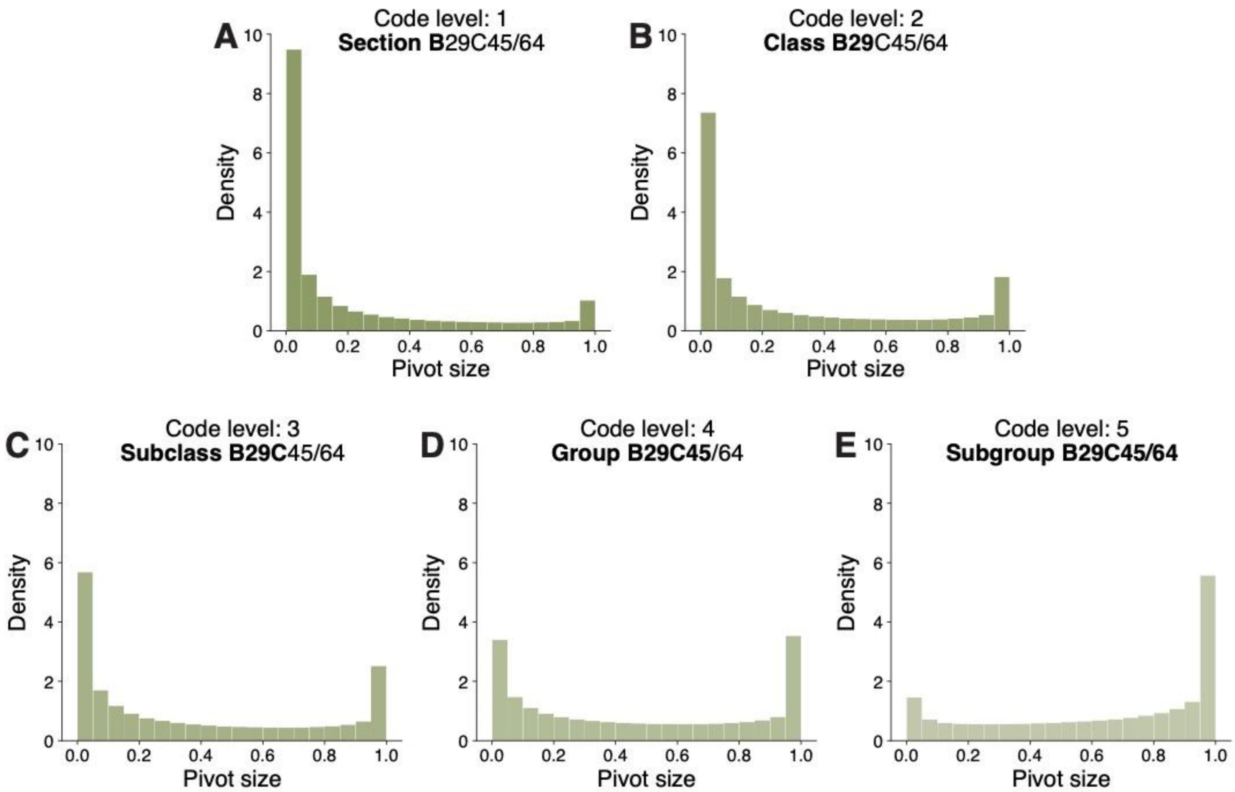

Figure S2: Quantifying pivot size using various levels of patent technology classification. For historical patents granted from 1975-2015, the pivot size distribution is bimodal, with more weight on pivots of size zero and one. The average pivot size increases as the definition of technology class used to calculate pivoting narrows. The available levels of technology class are: (**A**) 9 sections (e.g., “B”), (**B**) 128 classes (e.g., “B29”), (**C**) 662 subclasses (e.g., “B29C”), (**D**) 9,987 groups (e.g., “B29C45”), and (**E**) 210,347 subgroups (e.g., “B29C45/64”). The main analysis in Figures 1 and 2 use level-4 groups to define pivot size.

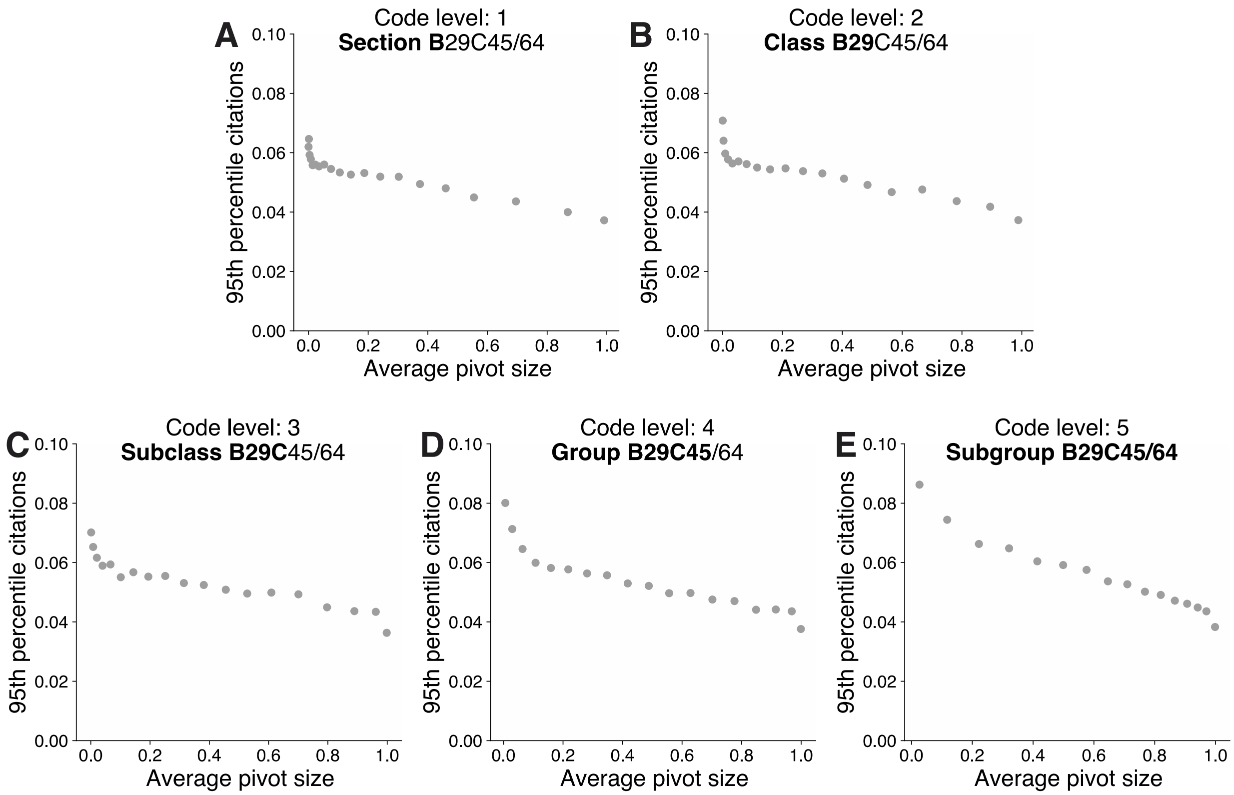

Figure S3: The pivot penalty with various technology levels. The probability of being a highly cited patent is decreasing in pivot size for all technology code levels used to define pivoting. The difference in impact between the highest and lowest pivot size is (**A**) smallest when using broad level-1 classes and (**E**) largest when using narrow level-5 subgroups.

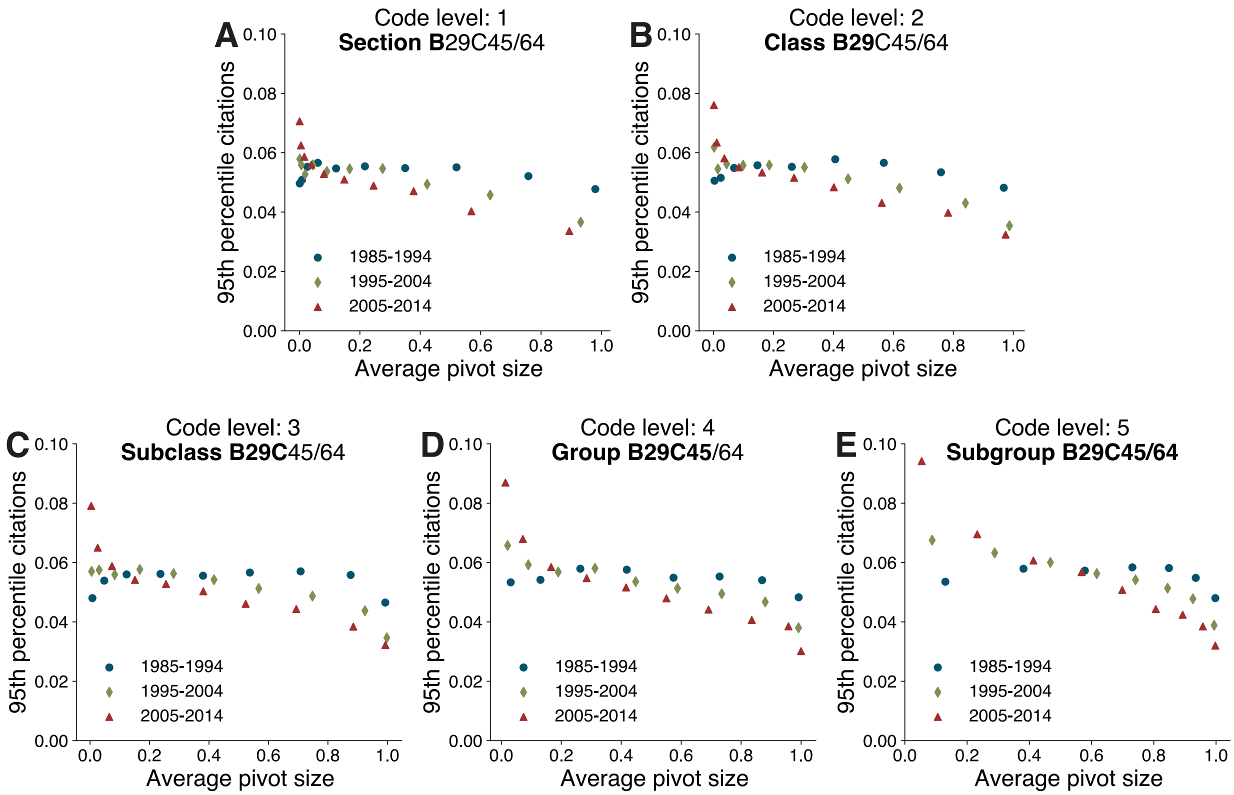

Figure S4: The pivot penalty over time with various technology levels. The slope of the pivot penalty is increasing over time, regardless of which level of technology code is used to define pivot size. The increase in slope over time is (**A**) smallest when using broad level-1 sections and (**E**) largest when using narrow level-5 subgroups.

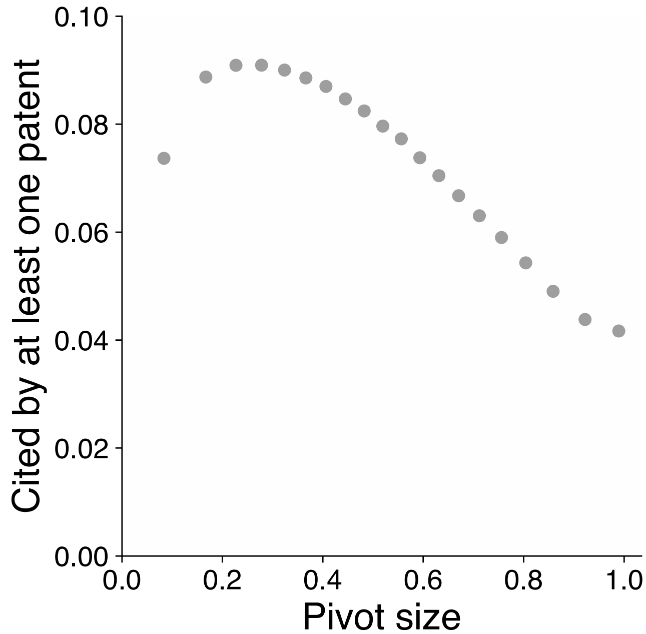

Figure S5: Patent references to papers. The probability that an academic paper is referenced by at least one patent is falling in average pivot size. This panel includes 37 million papers published from 1970-2019.

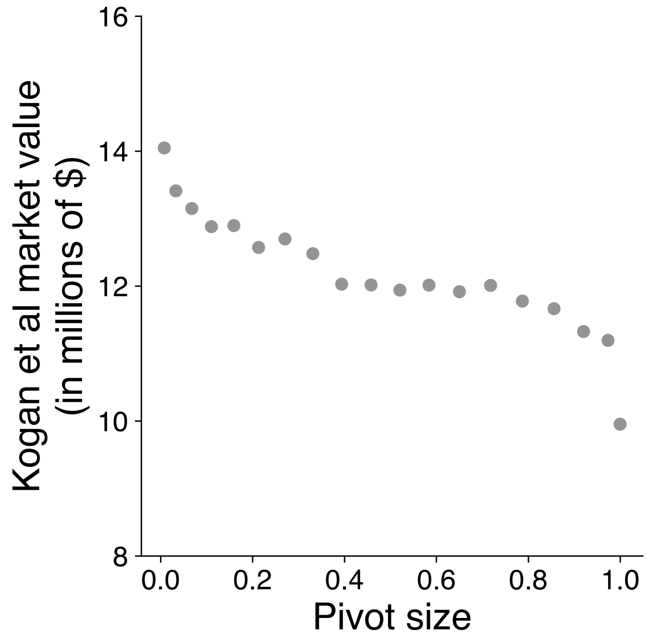

Figure S6: Patent market value. The estimated market value of patents is decreasing in average pivot size. Market value is estimated using changes in stock prices around the announcement of patent grants for public companies. The sample is 802,599 patents published between 1980 and 2015 that were granted to public corporations. Market valuations as calculated by Kogan et al (2017).[10]

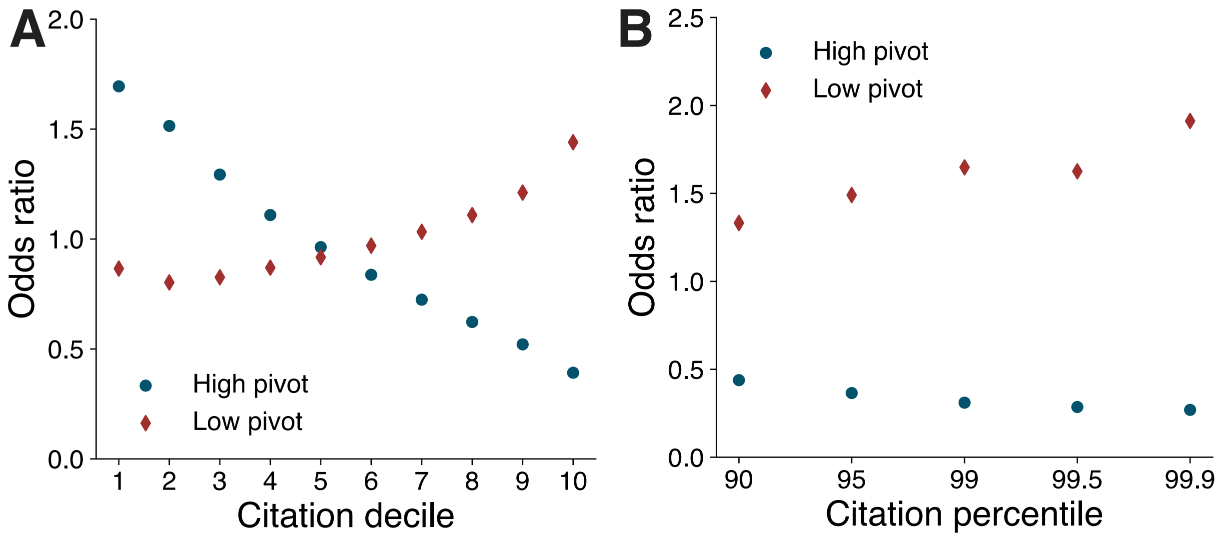

Figure S7: Probability of high and low pivot across citation distribution. (A) The x-axis groups all papers into deciles by the number of citations within year and L0 field. The y-axis reports the odds ratio that a low and high pivot paper will be found in that citation bin. The low (high) pivot odds 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 90th and the 99.9th percentile of citations.

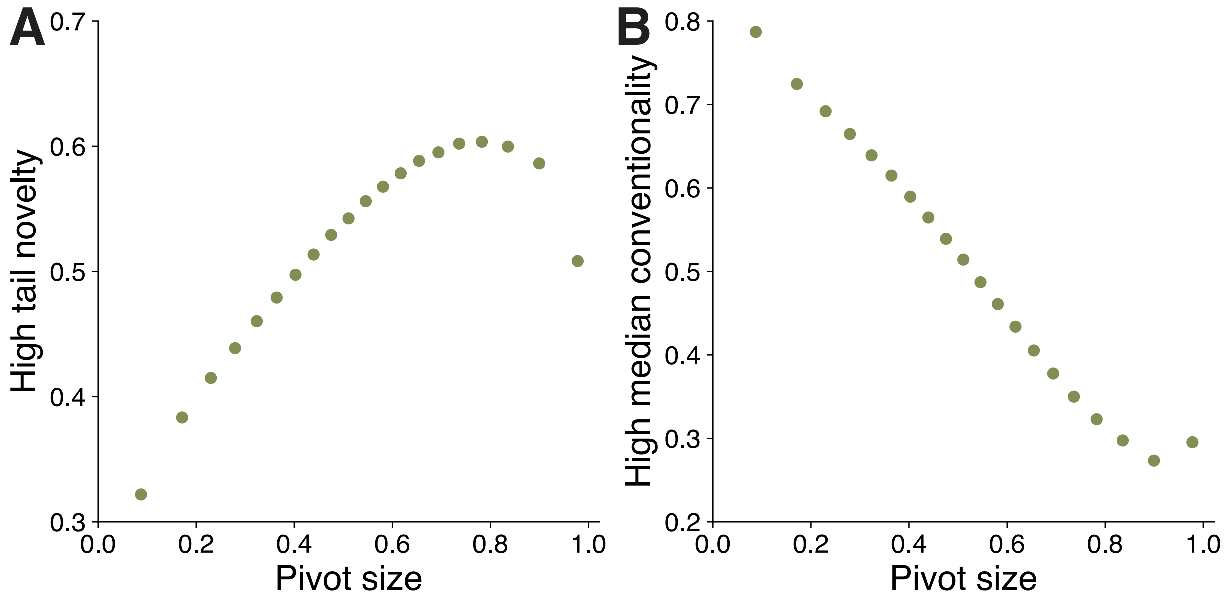

Figure S8: Novelty, conventionality and pivot size. (A) Novelty is increasing with pivot size while **(B)** conventionality decreases. Measures are calculated using combinations of references in new academic papers[5]. A researcher who is pivoting not only does something new personally, but also tends to combine prior knowledge in a way that is unusual in science. At the same time, high pivots are associated with distinctly low conventionality, consistent with a weaker grounding in conventional domain knowledge.

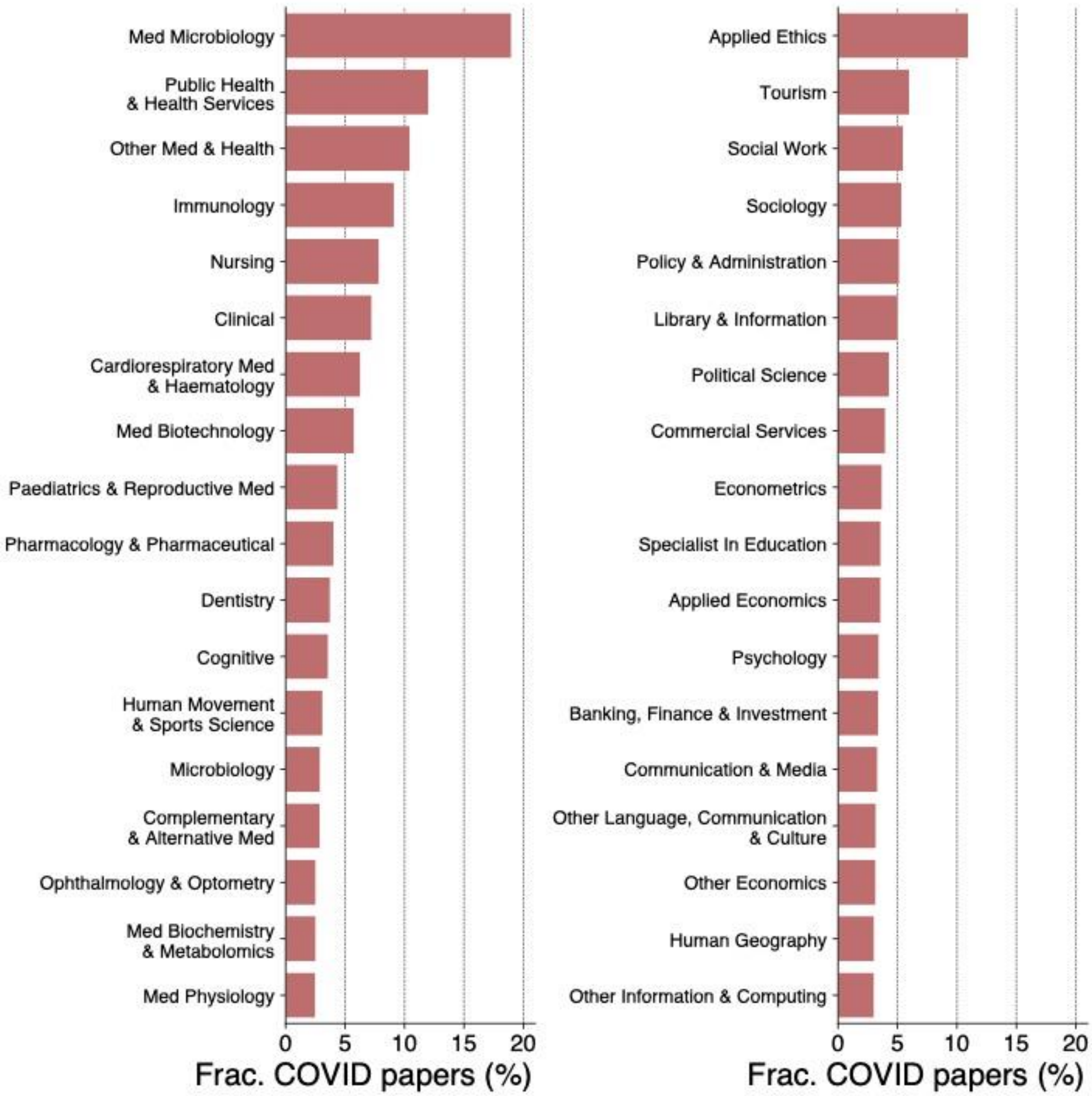

Figure S9: COVID share by subfield. This figure reports COVID-19 papers as a fraction of all 2020 publications in specific level-1 fields. Presented here are the 20 medical and 20 non-medical level-1 fields that have the highest fraction of COVID papers.

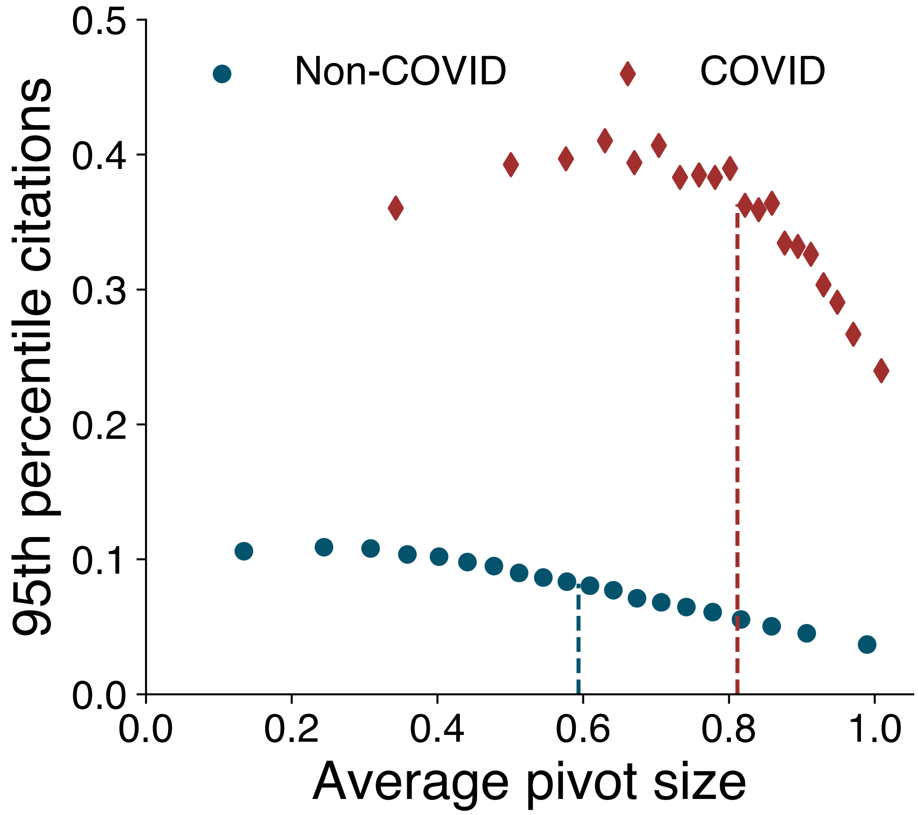

Figure S10: Hit rates and pivot size using a paper's citations within 2020. The mean paper-level hit rate is presented against pivot size for COVID-19 papers (red) and all other papers (blue) published in 2020. Hit rates are determined at the paper-level, using citations received by the paper through the end of 2020.

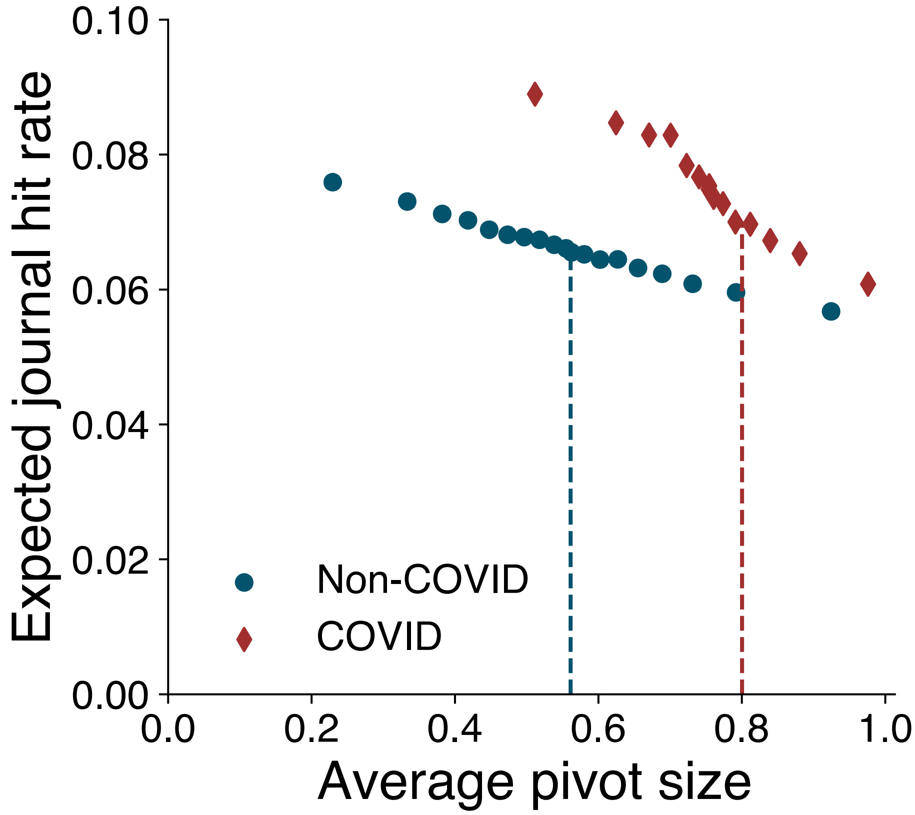

Figure S11: Hit rates and pivot size using individual fixed effects. This figure follows the pivot-impact analysis shown in Fig. 3E. In this version, we use a regression adjustment for individual fixed effects within each series to control for unobservable factors that might drive pivot size and impact differentially across researchers.

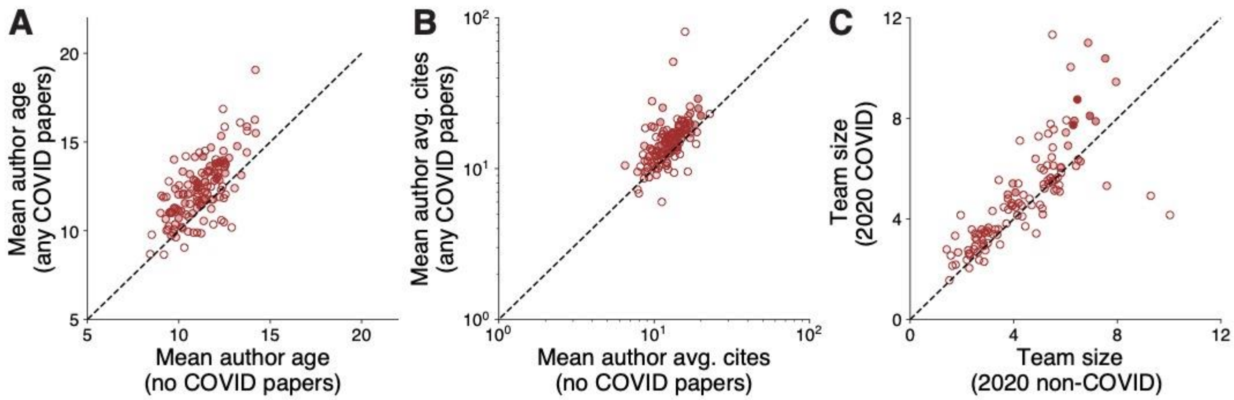

Figure S12: Pivoting characteristics by field. These plots examine paper and author features by field, comparing COVID and non-COVID research among actively publishing scientists in 2020. Markers with darker shading indicate fields with more COVID publications. Authors are assigned to the level-1 field in which they have published the most. **(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.

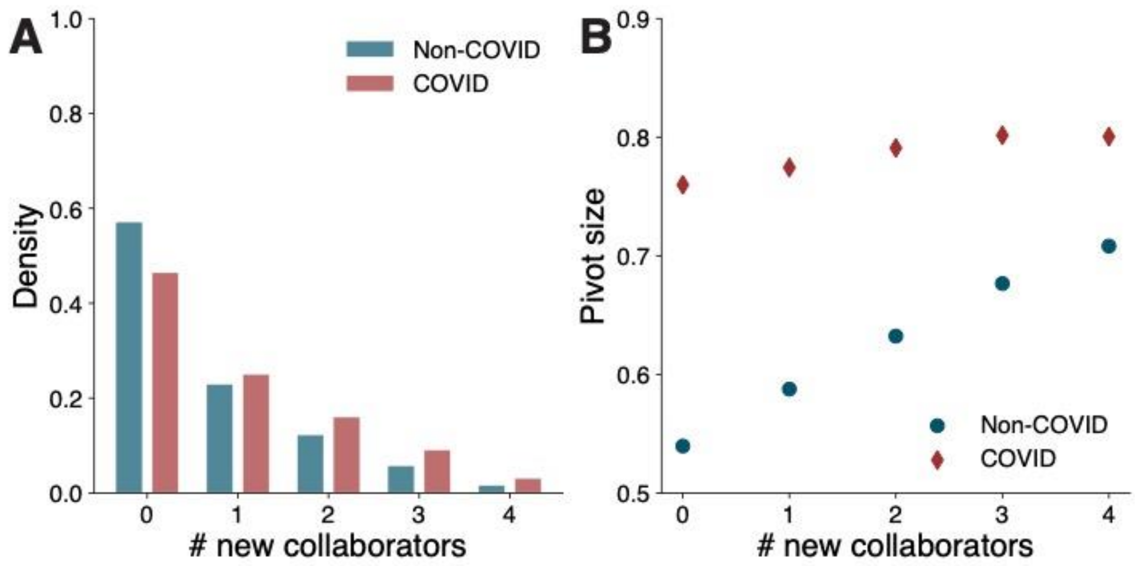

Figure S13: Pivots and new collaborators. These plots consider all 2020 publications with exactly five authors (similar results are found using different team sizes). **(A)** Papers with no new coauthors are the most common form, while **(B)** pivot size is increasing with the number of new coauthors.

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 95th 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 95th 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.

Outcome variable: 95th percentile of citations	(1)	(2)	(3)	(4)
Pivot Size	-0.0888***	-0.0467***	-0.0456***	-0.0332***
	(0.000316)	(0.000464)	(0.000500)	(0.000538)
Individual FE		X		
Individual X Field of Journal FE			X	
Individual X Journal FE				X
Observations	11,561,780	11,561,780	11,551,147	11,561,780
R-squared	0.006	0.236	0.318	0.464

Table S3: 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. 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. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

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