Different personal propensities among scientists relate to deeper vs. broader knowledge contributions

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Scientific journal publications, and their contributions to knowledge, can be described by their depth (specialized, domain-specific knowledge extensions) and breadth (topical scope, including spanning multiple knowledge domains). Toward generating hypotheses about how scientists' personal dispositions would uniquely predict deeper vs. broader contributions to the literature, we assumed that conducting broader studies is generally viewed as less attractive (e.g., riskier) than conducting deeper studies. Study 1 then supported our assumptions: the scientists surveyed considered a hypothetical broader study, compared with an otherwise-comparable deeper study, to be riskier, a less-significant opportunity, and of lower potential importance; they further reported being less likely to pursue it and, in a forced choice, most chose to work on the deeper study. In Study 2, questionnaire measures of medical researchers' personal dispositions and 10 y of PubMed data indicating their publications' topical coverage revealed how dispositions differentially predict depth vs. breadth. Competitiveness predicted depth positively, whereas conscientiousness predicted breadth negatively. Performance goal orientation predicted depth but not breadth, and learning goal orientation contrastingly predicted breadth but not depth. Openness to experience positively predicted both depth and breadth. Exploratory work behavior (the converse of applying and exploiting one's current knowledge) predicted breadth positively and depth negatively. Thus, this research distinguishes depth and breadth of published knowledge contributions, and provides new insights into how scientists' personal dispositions influence research processes and products.

personality | goal orientation | competitiveness | exploration | scientific performance productivity

> A human being should be able to change a diaper, plan an invasion, butcher a hog, conn a ship, design a building, write a sonnet, balance accounts, build a wall, set a bone, comfort the dying, take orders, give orders, cooperate, act alone, solve equations, analyze a new problem, pitch manure, program a computer, cook a tasty meal, fight efficiently, die gallantly. Specialization is for insects.
>
> Robert Heinlein

> A really definitive and good accomplishment is today always a specialized act.
>
> Max Weber

Scientific research is an enterprise crucial to the planet, economies, institutions, cultures, and the people who engage in it. Scientists approach their work with not only differing backgrounds but disparate personal preferences and work styles. If we want to more fully understand scientific progress, we should try to develop a better understanding of why and how scientists pursue their research in the ways that they do.

In this study, we ask why some scientists tend to pursue and publish deeper contributions to knowledge within their specialties, whereas others span the boundaries of multiple knowledge domains and publish broader contributions. We believe that, armed with information about personal tendencies such as those revealed in this study, scientists can make more conscious, informed, and deliberate decisions about project choice and design, as well as their professional goals and approaches to their work.

With some exceptions (1, 2), prior studies of research productivity typically have used aggregate measures of output, such as numbers of articles published, patents granted, and genes sequenced (3, 4). The study reported here advances our understanding of scientific research in two main ways. First, we investigate not the quantity of research but its nature, by distinguishing between the depth and breadth of scientists' publication records as aggregated over a 10-y period. Second, we document how scientists' personal propensities relate differentially to these two research characteristics. For control purposes we drew from a single population of scientists: published diabetes researchers. Diabetes has a large and active research community, is one of the oldest-known and most important diseases, and has a comprehensive database.

We assess depth and breadth of publication portfolios, rather than categorize scientists as specialists and generalists, for several reasons. First, this approach highlights the nature of knowledge contributions rather than placing individuals into fixed categories. Second, the depth and breadth dimensions reflect the continuous (as opposed to categorical) nature of most work output. Third, our treatment of deep and broad contributions avoids implying that productive "types" of researchers cannot change their approaches to their work if they decide they want to.

The depth/breadth distinction in scientific research may be of even greater importance and interest now than in the past. In academic environments, the intellectual endeavor has changed over the centuries, and perhaps is again changing profoundly.

Significance

Scientists' productivity usually is measured with a single metric, such as number of articles published. Here, we study two dimensions of scientists' knowledge contributions in 10-y publication records: their depth and their breadth. Study 1 shows that scientists view pursuing a deeper research project to be more attractive than pursuing a broader project; for example, scientists viewed broad projects as riskier and less important than deeper projects. Study 2 shows that scientists' personal dispositions predict the aggregated depth vs. breadth of their published articles. Armed with such knowledge, scientists can strategically consider the desired nature of their research portfolios, criteria for choosing and designing research projects, how to compose research teams, and the inhibitors and facilitators of boundary-crossing research.

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Whereas scholars historically were educated in a wide variety of disciplines, today they tend more toward deep specialization than boundary-spanning breadth (5–7). At the same time, many universities are attempting to place greater emphasis on broader, integrative research that bridges knowledge boundaries (8, 9). Particularly, if such work is not explicitly supported and rewarded, researchers' personal dispositions will determine whether or not such contributions actually emerge, or more accurately, how much of each dimension emerges.

Deep and broad knowledge contributions are not mutually exclusive but they can be distinguished, as we do in this study, using Medical Subject Headings (MeSH) that describe the topics covered by medical publications. We operationally define broad knowledge contributions (hereafter, breadth) as the extent to which publications bridge or pertain to multiple knowledge domains: the greater the number of and distinction between domains, the greater the breadth. In contrast, deep knowledge contributions extend knowledge within more specialized knowledge domains. The more extensive the domain-specific additions to knowledge, the greater the depth.

Scientists, although facing standard performance expectations, such as collecting data, writing manuscripts, and publishing findings, exert influence on the nature of the projects that they pursue. Researchers work under strong demands *to* produce, but often have freedom to determine *how* and *what* they produce (10). With clear demands for outcomes (publications), but with behavioral inputs less precisely specified (11), scientists have an opportunity to express their individual preferences. In such circumstances, personal proclivities can lead to different types of research projects and publications. When unconstrained by the work environment, people express behaviorally their personal tendencies because doing so has intrinsic value (11). Furthermore, although one publication does not necessarily reveal personal proclivities toward depth or breadth, multiple publications over time can and likely do.

Reward systems, norms, and other factors are likely to support and encourage deep specialization more than generalism across multiple knowledge domains (e.g., ref. 12). Economists long have valued work specialization for the focused expertise, depth, and efficiency that it provides. Career-focused students, engineers, and businesspeople acquire deep technical or functional expertise as a matter of course. Scientists appreciate and pursue deep expertise in a specific domain (13), and deep expertise typically is rewarded, in part because of beliefs that it has a strong relationship with innovation (14) and institutional preeminence (7).

Moreover, many observers (e.g., refs. 5–7, 15) note that intellectual balkanization and other barriers make it costlier and riskier (e.g., in terms of time, effort, and difficulty finding a publication outlet) to pursue intellectual breadth by crossing knowledge boundaries. More than extending knowledge within a specialized domain, conducting research that bridges two or more knowledge domains requires acquiring and applying different content and methodological expertise, or at least considering multiple styles of thought, research traditions, techniques, and discipline-specific terminologies that are difficult to translate across domains (8). Therefore, we assumed—and supported empirically with the first study reported below—that scientists generally tend to perceive the more focused pursuit of intellectual depth within knowledge domains as less risky, less costly, more instrumental, and more worth the investment of personal resources than the broader pursuit of domain-bridging research.

Nonetheless, some scientists pursue breadth rather than or in addition to depth. We propose that certain personal propensities will help to explain why some scientists are more likely than others to pursue breadth despite the constraining and inhibiting factors discussed above. In selecting personal tendencies to study, we chose pairs of variables in which one disposition would be more likely to predict depth and the other more likely to predict breadth. We considered first the "Big Five" personality traits, a comprehensive set that has emerged from decades of trait studies (16). We selected conscientiousness and openness to experience because they are generally relevant to producing published research and because they have different implications for publishing deeper vs. broader research. The other three Big Five traits—agreeableness, extraversion, and emotional stability—are conceivably and sometimes relevant to research productivity, but less so overall and in distinctively predicting depth vs. breadth (11).

The behaviors of "conscientiousness" include attention to detail, precision, rule-following, and high-quality task completion, whereas "openness to experience" includes desire to learn and creativity. All of these behaviors are important to engaging (and engaging successfully) in the research process; they provide motivation to pursue new knowledge, initiate projects, design studies, and pursue them to publication. However, we further expected that conscientiousness and openness to experience would hold very different implications for depth and breadth. Because conscientiousness suggests rule following and dependability—which imply compliance with professional norms, desire for steady progress toward completion, and a preference for direct and efficient paths to task accomplishment—we predicted that individuals higher in conscientiousness would more likely pursue depth within knowledge domains and avoid the higher costs and risks of moving beyond their specialties into broader, boundary-crossing pursuits. On the other hand, openness to experience is characterized by independence, broadmindedness, and unconventionality; we expected that higher openness would motivate boundary-spanning behaviors, resulting in research of greater breadth. Thus, conscientiousness should relate to depth more than to breadth, and openness to experience to breadth more than to depth.

A second pair of personal dispositions, learning and performance goal orientations, are important achievement-related motives (17). "Performance goal orientation" (PGO) concerns a desire to perform well and to demonstrate good performance to others, and predicts choosing tasks with which one is already familiar and confident in his or her ability to perform at high levels. "Learning goal orientation" (LGO) is related to a desire to learn by tackling new challenges, as well as to willingness to work in unfamiliar knowledge domains in which one is at a relative disadvantage. LGO also relates to a variety of adaptive thoughts and behaviors that would aide boundary-bridging research, such as persisting in the face of difficulties and engaging in learning strategies that are particularly useful when venturing into new domains.

High LGO leads to better performance than does high PGO in challenging situations that require people to embrace new learning, which includes research generally but of which bridging knowledge boundaries is a particularly strong example. High PGO individuals would prefer to apply what they know in less risky, more focused, deeper ways. Therefore, we predicted that PGO would relate most positively to deeper knowledge contributions, and LGO most positively to broader knowledge contributions.

The third pair of personal dispositions included competitiveness and exploratory work behaviors. We investigated "competitiveness" because of its prominent role in the scientific endeavor. We expected higher levels of competitiveness to motivate deeper work because depth is less costly, less risky, and has a higher probability of success, and because one is at a competitive disadvantage when crossing into new knowledge domains. "Exploratory work behavior" (exploration) is the search for and pursuit of new knowledge via new combinations and alternatives; its converse, exploitation, is the application, refinement, and extension of current competencies (18, 19). Exploration includes engaging in a greater variety of new challenges, venturing into more distal unknowns, seeking novel approaches to work, and synthesizing ideas. Exploitation (low levels of exploration; see *Supporting Information* for more on this) suggests the opposite.

Therefore, we predicted that exploration would positively predict broader knowledge contributions and negatively predict deeper knowledge contributions.

In a brief Study 1, we used hypothetical project descriptions to test the assumption guiding our predictions: that researchers generally find deep projects more appealing than broad projects. Study 2, with a different sample, then tested the predictions by matching questionnaire data from active diabetes researchers with 10 y of independently assessed data indicating the research topics of their articles. Our bibliographic approach allowed us to control for overall productivity and thereby examine separately the depth and breadth of each researcher's 10-y published output. We controlled for several demographic and employment variables, for breadth when assessing depth, and for depth when assessing breadth. We also controlled statistically, in separate analyses, for network centrality and total number of publications. Network centrality indicates an author's position in a coauthorship network and is an indicator of influence in the field (20).

Our Study 2 results clearly indicate distinctive individual-difference foundations of depth vs. breadth in knowledge contributions. First, though, Study 1 tested our working assumptions about scientists' perceptions of deep vs. broad research projects.

Results

Study 1. In a simple test of scientists' appraisals of deep, specialized studies vs. broader studies that span multiple domains, we created brief hypothetical descriptions of two studies (Fig. 1; see details in *Supporting Information*). Counterbalancing the sequence of the descriptions in a sample separate from our primary (Study 2) sample, we found that these scientists considered the broader study to be riskier (means = 4.61 vs. 3.15; $t = 12.94$, $P < 0.001$), a less significant opportunity (5.17 vs. 5.83; t = 6.13, $P < 0.001$), and of lower potential importance (5.35 vs. 5.72; $t = 3.47$, $P < 0.001$). They reported being less likely to pursue the broader project (on a 100% probability scale, 59.9 vs. 73.5; $t = 14.45$, $P < 0.001$). Forced to choose, 64% chose the deep project and 33% ($t = 30.12$, $P < 0.001$) chose the broad project (3% were missing). These results support the assumptions underlying our Study 2 predictions, that the perceived risk/return trade-off generally favors choosing depth over breadth.

Study 2. We conducted confirmatory factor analysis to assess the adequacy of the measurement component of the proposed model and to evaluate the model relative to alternative models (21). A six-factor model, in which items measuring our six self-reported dispositional variables loaded on separate correlated factors, had a significant χ^2 test [χ^2 (175) = 615.09, $P < 0.001$], and exhibited good fit [comparative fit index (CFI) = 0.90, root mean square error of approximation (RMSEA) = 0.07]. Moreover, the six-factor model's standardized loadings were strong and significant, ranging from 0.50 to 0.93 (all $P < 0.01$). We compared the hypothesized measurement model to a one-factor model (22) in which all of the items loaded on a common factor [χ^2 (202) = 1315.5, $P < 0.001$, CFI = 0.72, RMSEA = 0.17] and found that the hypothesized six-factor model fit the data better than the one-factor model [χ^2 (27) = 700.41, $P < 0.001$].

Internal reliabilities, means, SDs, and correlations among all study variables are reported in *Supporting Information*. General population norms were not available for assessing this sample's mean scores, but it is possible that researchers as a group are higher than average on traits such as openness and LGO. Thus, restriction of range may have reduced the magnitude of the correlations with depth and breadth observed here. All of the interfactor correlations were below the recommended level of 0.70 (23). As an additional check, we examined the variance inflation factors associated with each predictor and found all to be less than 10. We therefore inferred that multicollinearity and associated problems were not likely to bias our results.

The two dependent variables, depth and breadth, were correlated positively (r = 0.59), and therefore we analyzed them separately (in each case, controlling for the other) rather than using the same predictive model. Discriminant validity is supported by roughly 65% of variance unshared. At the same time, sharing 35% variance renders the statistical tests somewhat conservative, making the many significant and distinguishing relationships particularly noteworthy.

Table 1 (for depth) and Table 2 (for breadth) show the regression results. With controls including network centrality, conscientiousness negatively predicted breadth (B = −0.091 $P < 0.01$) (Table 1), whereas openness to experience positively predicted both breadth (B = 0.276; $P < 0.001$) (Table 2) and depth (B = 0.152, $P < 0.001$) (Table 1).

For the two goal orientations, the results confirm both predicted positive relationships: performance goal orientation with deeper knowledge contributions (B = 0.208; $P < 0.001$) (Table 1) and learning goal orientation with broader knowledge contributions (B = 0.203; $P < 0.001$) (Table 2). In addition, as expected, PGO did not predict breadth and LGO did not predict depth. Thus, each goal orientation predicted one (different) research dimension and not the other.

Regarding the final two predictors, competitiveness positively predicted depth (B = 0.151; $P < 0.01$) (Table 1), and exploration positively predicted breadth (B = 0.139; $P < 0.01$) (Table 2) while negatively predicting depth (B = −0.188; $P < 0.001$) (Table 2). *Supporting Information* has details showing that all results were replicated when controlling for total publications rather than network centrality.

Discussion

By investigating deep and broad knowledge contributions and related personal dispositions, our study contributes to our understanding of the nature and processes of scientific research. The scientists in Study 1 clearly favored a hypothetical deep research project over an otherwise-identical broad project; they viewed the broader study as costlier, riskier, less of an opportunity, and having a lower probability of success. The scientists also reported a higher likelihood of pursuing the deeper than the broader project, and a greater percentage chose the deeper project in a forced choice. These differing appraisals support the assumptions underlying our choices of personal dispositions that would differentially motivate the pursuit and publication of deeper vs. broader research.

Study 2, with tests rendered conservative by controlling for demographic variables, network centrality, and total number of publications, then confirmed that different dispositional tendencies relate to published articles' depth and breadth. The aggregated depth of knowledge contributions relates positively to competitiveness, openness to experience, and performance goal orientation. In contrast, breadth relates positively to LGO and openness to experience. Conscientiousness predicts breadth negatively, and exploratory work behavior predicts breadth positively and depth negatively. Thus, not only do the predictors of depth and breadth differ, but each differs in its predictive power and sometimes direction.

Put another way, deep knowledge contributions are facilitated by certain personal tendencies and inhibited by others, whereas broad knowledge contributions are inhibited and facilitated by certain other dispositions. Openness to experience is the only one that aids both deep and broad output. Conscientiousness

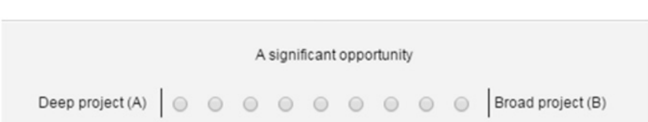

Fig. 1. Study 1 scale format.

Table 1. Depth regression analysis

Dependent variable: Depth	Standardized coefficients: Model 1 controls Coefficient	SE	Model 2 full model Coefficient	SE
Constant	−6.580	(8.598)	5.461	(8.206)
Centrality	0.194***	(0.113)	0.210***	(0.106)
University researcher	−0.013	(0.106)	0.011	(0.099)
Sex	−0.064	(0.097)	−0.037	(0.095)
US researcher	0.012	(0.098)	−0.049	(0.094)
Date of first publication	0.034	(0.004)	−0.043	(0.004)
Conscientiousness			0.063	(0.050)
Openness to experience			0.152***	(0.055)
Performance goal orientation			0.208***	(0.047)
Learning goal orientation			−0.006	(0.058)
Exploration			−0.188***	(0.042)
Competitiveness			0.151**	(0.033)
R^2	0.080		0.210	
Improvement over base (ΔR^2)			0.130**	

*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$; SEs in parentheses.

hinders breadth, whereas LGO aids it. PGO and competitiveness aid depth. Exploratory work behavior aids breadth and hinders depth, whereas its converse, the application and exploitation of current knowledge, aids depth.

Knowing the tendencies revealed in this study, scientists can make deliberate, informed choices about research goals and processes at personal, team, and administrative levels. Scientists' decisions about which projects to pursue and how to design them of course are driven by many factors, including topical interests, methods, opportunities, constraints, and reward systems. Sometimes such decisions are made based on explicitly considered criteria, whereas other times they emerge more organically or implicitly and without full deliberation. Explicitly adding depth and breadth as decision criteria can expand the conversation for individuals, teams, institutions, and entire fields.

Every researcher has certain dispositional tendencies toward or away from depth and breadth, and when making decisions may or may not be aware of their own tendencies and those of their colleagues and disciplines. These considerations can help scientists think strategically about the depth and breadth of their past and current work, and whether and how to change the mix for the future. Interested scientists can identify their personal tendencies and continue on the same deep or broad path or deliberately (as they desire) modify their research goals, alter previous tendencies, and apply different work styles that are more or less conducive to depth or breadth.

One methodological issue is that the personal dispositions were measured at the end of the 10-y period of published research. As such, we are unable to make absolute claims about causal directionality. Lessening this concern, the dispositions are considered to be stable (e.g., refs. 6, 24, and 25). The known stabilities of the dispositions that we studied, combined with the fact that their measures (in all studies, whenever administered) represent summary descriptions of past behaviors (e.g., refs. 16 and 26–30), support the likelihood that research depth and breadth are outcomes of the dispositions studied here, while paving the way for future studies that more fully examine the causal directions and mechanisms driving our findings.

We controlled statistically for scientists' network centrality, because choices to undertake deep or broad projects and the outcomes of those projects are partly a function of the people with whom a person works. Using this control variable was a strength of this study, but future work can deal more thoroughly with the role of research team composition as defined by the personal dispositions studied here and the conversations that teams engage in. We submit that our data captured the participants' broader behavioral patterns, including choices of coauthors as well as projects, thus maintaining the validity of the results. Nonetheless, investigators in future depth and breadth studies should further examine team characteristics and processes.

A potentially important study limitation is the nature of the boundaries that our sample of scientists crossed in their broader research. We studied a large diabetes research community, spanning many medical boundaries, but our data did not cross nonmedical disciplinary chasms, such as social and biophysical sciences (31), or combine theoretical perspectives with practical methodologies (32). However difficult it may be to cross medical boundaries, it likely is more difficult yet to conduct and publish work that is truly interdisciplinary in ways that broadly and systemically address the "wicked problems" of the world. Future research needs to more thoroughly examine the unique challenges of large-scale interdisciplinary work.

We did not study potential consequences of depth and breadth (1, 2, 33), so future research needs to explore the various direct and moderated effects of deep and broad knowledge contributions. At the same time, we should continue to identify additional psychological, behavioral, and environmental predictors of each. Combined, we will gain a more complete understanding of their distinct nomological nets.

We do not suggest that either depth or breadth is "better" than the other; nothing about our data bolsters or disputes the value of deeper (broader) research. Each has potential advantages and disadvantages, and is more or less useful depending on objectives and context. However, opinions can run strong: "Among sociologists, interdisciplinarity is lauded as an ideal, scorned as a threat, and embraced as a practice" (34). A national survey in the United States indicates that a majority of college and university faculty agree with a statement that interdisciplinary knowledge is better than knowledge contained by a single discipline (8), but our data indicate several perceptions that inhibit boundary crossing. Whereas the relative advantages and disadvantages of depth and breadth need empirical examination (8), many observers worry

Table 2. Breadth regression analysis

Dependent variable: Breadth	Standardized coefficients: Model 3 controls Coefficient	SE	Model 4 full model Coefficient	SE
Constant	3.626	(0.221)	−4.400	(0.533)
Centrality	0.240***	(0.117)	0.496***	(0.106)
University researcher	0.105	(0.111)	0.100	(0.100)
Sex	−0.127	(0.101)	−0.072	(0.095)
US researcher	−0.170	(0.102)	−0.073	(0.094)
Date of first publication	−0.125*	(0.050)	−0.124*	(0.049)
Conscientiousness			−0.091*	(0.051)
Openness to experience			0.276***	(0.055)
Performance goal orientation			−0.011	(0.017)
Learning goal orientation			0.203***	(0.058)
Exploration			0.139**	(0.042)
Competitiveness			0.064	(0.034)
R^2	0.152		0.251	
Improvement over base (ΔR^2)			0.099***	

*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$; SEs in parentheses.

about how deep overspecialization creates disconnected silos of thinking that inhibit innovation and stifle inquiry on topics outside the narrow confines of each discipline (6, 7, 34–37). Thus, the National Academy of Sciences stated that "to hinder [interdisciplinary] activity is to diminish our ability to address the great questions of science and to hesitate before the scientific and societal challenges of our time" (37).

Conclusion

Varying emphases on depth and breadth in the training and development of, and reward systems for, scientists will likely affect both the rate and the nature of scientific progress. Pending rigorous studies of the relative advantages and disadvantages of deeper and broader research portfolios, including contingency factors, we have attempted to remain agnostic about their relative importance. Scholars currently are questioning the nature of publication demands and whether they meet today's most important needs. For example, sociobiologists warn that professional atomization and thinking in silos work against unifying and leveraging together centuries of independently accumulated knowledge and discoveries, and that the discipline-based obstacles to synthesis and integration must be torn down in order for humanity to progress (6, 7, 16).

The research productivity of scientists is of long-standing academic interest for many reasons, including its importance to society as a whole (38). This study contributes to our understanding of two distinguishable characteristics of scientific knowledge. The PubMed database and the participation of the scientists in this study allowed us to validate the depth/breadth distinction and gain new understanding of several important personal tendencies, thereby offering significant contributions to the authors' fields (strategic management and organizational behavior). Scientists, armed with this knowledge, can make informed and strategic decisions about projects and approaches to their work. Needed now are investigations into important related areas, such as (*i*) the consequences, not just the predictors, of depth and breadth; (*ii*) contingency factors influencing their causes and consequences; and (*iii*) deep and boundary-crossing work beyond that studied here, to more fully understand both plumbing and bridging of other knowledge domains.

Materials and Methods

Study 1's methodological details are described in *Supporting Information*. For Study 2, we gathered both primary and secondary data about active medical researchers. This research was approved by the University of Virginia's Institutional Review Board. All participants provided written informed consent prior to participating.

Participants and Procedure. The first step in identifying potential study participants was to choose a particular research community on which to focus. It was appropriate and helpful to use a single broad research domain for several reasons. First, we needed a distinct population of researchers from which we could randomly extract a sample of survey recipients. Second, significant variance exists across scientific communities regarding the nature of the publication process (publication outlets, theoretical versus experimental focus, rigor, publication time lag, focus on human versus nonhuman subjects, and so forth). After speaking with multiple industry experts, we chose the diabetes research community for our sample. Diabetes is one of the oldest known diseases and has one of the largest research communities. Over the last 10 y, more than 40,000 different authors have published diabetes research. Through a keyword search in the PubMed database, we identified just over 15,000 scientists who had published diabetes-related research between 2001 and 2011. From this population, we randomly selected researchers to participate in two separate studies. We collected roughly 5,000 email addresses to create our sample. Among our final Study 2 sample of 466 participants, 57% were male, 60% were located in the United States, and the mean age was 49 y.

Even though most of the dispositional measures are well validated, we piloted them with two active medical researchers to help ensure the content and face validities for this sample. We asked them to answer all of the questionnaire items, provide feedback about their design and wording, and verify the relevance of the questionnaire. The pilot participants reported understanding all of the items, and their suggestions regarding details enabled us to refine and finalize the questionnaire.

Measures.

Control variables. We included a variety of control variables in Study 2: sex, employment affiliation (university, hospital, pharmaceutical firm, and research center), residence (United States vs. non-United States), age, tenure in the field (based on the date of the researcher's first publication), network centrality, and total publications. The demographic controls were self-reported by our respondents, but the information was validated using third-party scientific profiles.

As mentioned, we began with a list of the population of diabetes researchers over the 10-y period. From these data, we constructed a coauthor network for each researcher and calculated a betweenness centrality score using the software program NodeXL, which can accommodate large lists of participants. Betweenness centrality is a measure of an author's positional advantage, or power, such that actors with high scores sit at prominent positions in the diabetes coauthorship network. Such authors are able to translate this brokerage role into power and influence in their fields (20). This measure allowed us to control for and to rule out alternative social network explanations for our results.

We also replicated all results when controlling for researchers' overall productivity (total publication count). In these analyses, reported in the supporting information, we controlled for total publications and not for network centrality, as these two variables were correlated 0.78. Whether controlling for network centrality or total publications, all results were the same.

Questionnaire measures. Individual differences were assessed via self-report measures, all of which had strong psychometric properties. We measured conscientiousness and openness to experience with their 10-item subscales of the International Personality Item Pool inventory, used widely to assess the Big Five. The International Personality Item Pool inventory uses the stem "I see myself as someone who…" followed for conscientiousness by items such as: "is always prepared," "pays attention to details," "likes order," and "is exacting in my work." Seven-point Likert scales ranged from 1, disagree strongly to 7, agree strongly. The coefficient α for conscientiousness was 0.84.

For openness to experience, sample items include: "is full of ideas," "spends time reflecting on things," "has excellent ideas," and "has difficulty understanding abstract ideas" (reverse scored). Coefficient α was 0.78.

For performance and learning goal orientations, we used the five items of the performance-prove orientation subscale and the six items of the LGO subscale of the work domain goal orientation instrument (39). Like conscientiousness and openness to experience, stabilities of both of these goal orientations are known to be high (22). Sample items for PGO are: "I would rather prove my ability on a task that I can do well than to try a new task" and "I try to figure out what it takes to prove my ability to others at work." Coefficient α was 0.83.

LGO sample items are, "I am willing to select a challenging work assignment that I can learn a lot from"; "I often look for opportunities to develop new skills and knowledge"; and "For me, development of my work ability is important enough to take risks." Coefficient α was 0.83.

We measured competitiveness with the four-item measure developed by Helmreich and Spence (40). Sample items are: "I feel that winning is important in both work and games" and "It is important to me to perform better than others on a task." Coefficient α was 0.89.

Using a separate sample of other medical researchers, we developed a new scale to measure exploratory work behavior. We wrote 10 nine-point semantic differential items based expressly on the original dichotomies described by March (19) in his descriptions of exploratory vs. exploitative activities by organizations, adapting the phrasing as needed for our sample of scientists.

We piloted the items with a small sample of local research scientists at the medical school of our university. Based on their comments and suggestions, we dropped one item. The final measure for the present sample used the stem, "In my research, I would rather…," followed by a nine-point semantic differential scale for each of the nine items. Examples of the paired anchors include: "refine and extend existing areas… seek path-breaking new research ideas," "explore new possibilities… exploit what I know," "refine my current research trajectory… search for new research paths," "be flexible… be focused." The final nine-item scale had a coefficient α of 0.76. To test for stability, 1 y later a subsample of 196 of the same respondents completed the scale again; the test-retest reliability was 0.75 and the coefficient α was 0.77.

Deep and broad knowledge contributions. Prior studies have examined the nature of a scientist's research by examining the word content of article titles (1, 2). We used the PubMed archival database and consultation with two medical experts who were familiar with it to generate depth and breadth scores for each scientist. Our operationalizations do not suffer from either the subjectivity of citation analysis or the inconsistency of traditional content analysis (41). We obtained the full list of 26,142 MeSH terms from the US National Library of Medicine. We then matched this MeSH term "master list" data to the publication records of the scientists in our sample. This process allowed us to use all MeSH term headings associated with each survey respondent for the 10-y period.

The final determinant of which keywords are assigned to each publication is made by the staff of the National Library of Medicine, not by the authors (42). Of particular importance is that the structure of the MeSH thesaurus provides a means for determining the depth and breadth of articles. The terms are arranged in a hierarchical, 2D array. The top level has 16 broad categories, each of which has 12 lower subcategories reaching greater and greater levels of depth and specificity.

To calculate breadth, we assigned 12 points to a MeSH term in the broadest, highest category in the database, 11 points for a term one level below, 10 for the next, and down to just 1 point for a term in the lowest, narrowest level. A MeSH term counted toward an author's breadth score only the first time it appeared on their record. We did this to ensure that we were measuring breadth not simply as a lack of depth; that is, multiple published papers on a single broad MeSH topic does not equate to bridging multiple broad knowledge boundaries. A paper that included (spanned) two top-level MeSH terms earned 24 breadth points, based on 12 points for each of the two categories. A paper listing two different level-two terms received 22 breadth points (11 for each term at that level), and one that spanned two level-three categories received 20 points. Points were added for every new term at every level. The average breadth scores were 94 per paper and 425 per respondent.

To determine depth, we gave each term a point value based on its location (level of depth) within the 12 hierarchical levels in the database. We assigned 12 depth points for a MeSH term in one of the deepest and most specific categories, 11 points for the next deepest, and continuing to just 1 depth point for a MeSH term in one of the highest, top-level categories. Again, as publications have multiple MeSH terms, each publication received a depth score that was the summation of the points for each MeSH term on the paper. The average depth scores were 56 per paper and 255 per respondent.

Analysis. In all analyses reported earlier we controlled statistically for network centrality, for depth when assessing breadth, and for breadth when assessing depth. In follow-up analyses, we controlled statistically for total number of publications as reported in the supporting information.

To test our predictions, we used ordinary least-squares regression with standardized variables. We used bootstrapped SEs in our regressions. Bootstrapping is a nonparametric approach for evaluating the distribution of a statistic based on random resampling. It estimates properties of an estimator (such as its variance) by measuring those properties when sampling from an approximating distribution. Bootstrapping provides a way to account for the distortions caused by the specific sample that may not be fully representative of the population.

As our unstandardized dependent variables are count variables, we also analyzed our data using negative binomial estimation. Results for all models are robust to this estimation.

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