Title

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Abstract: Has there been meaningful movement toward open science practices within the social sciences in recent years? Discussions about changes in practices such as posting data and pre-registering analyses have been marked by controversy—including controversy over the extent to which change has taken place. This study, based on the State of Social Science (3S) Survey, provides the first comprehensive assessment of awareness of, attitudes towards, perceived norms regarding, and adoption of open science practices within a broadly representative sample of scholars from four major social science disciplines: economics, political science, psychology, and sociology. We observe a steep increase in adoption: as of 2017, over 80% of scholars had used at least one such practice, rising from one quarter a decade earlier. Attitudes toward research transparency are on average similar between older and younger scholars, but the pace of change differs by field and methodology. According with theories of normal science and scientific change, the timing of increases in adoption coincides with technological innovations and institutional policies. Patterns are consistent with most scholars underestimating the trend toward open science in their discipline.

Introduction

Across many scientific disciplines there has been a movement to promote open science practices: posting data, code, and study materials online, and pre-registering studies, hypotheses, and analyses prior to a research study (Miguel et al 2014, Nosek et al 2015). In the social sciences for the past two decades, disciplinary organizations and journals have increasingly endorsed open science practices. More recently, cross-disciplinary social science organizations have been founded to accelerate awareness of open science and to provide training and supportive open science technologies, such as pre-registration platforms and open archives (Christensen, Freese and Miguel 2019). During this period, the social sciences have also grappled with debates and scandals surrounding the unavailability of original data, examples of publication bias, replication challenges, and in some cases data fraud (Bhattacharjee 2013, Borsboom and Wagenmakers 2012, Broockman, Kalla, and Aronow 2015, Carey 2011, Enders and Hoover 2004, Feilden 2017, Neuroskeptic 2012).

Beyond reducing the incidence of fraud (Simonsohn 2013), open science practices have been linked to the improved quality and credibility of research findings across fields. For example, study registration could increase the visibility of results, improving meta-analysis and reducing the selective reporting of null, unexpected or otherwise unfavorable results (Kaplan and Irvin 2015, de Vries et al 2018), and data sharing could increase later data re-use and article citations (Piwowar and Vision 2013).

Yet controversy and opposition have followed many research transparency proposals in the social sciences, particularly the use of pre-registration (Open Science Collaboration 2015, Gilbert et al 2016, Coffman and Niederle 2015). For instance, some worry that pre-registration might hamper creative research (Goldin-Meadow, 2016; Kupferschmidt, 2018). Others suggest that it maybe be used instrumentally or selectively, therefore doing little to remedy the underlying problems it was proposed to address (Claesen et al., 2019). Altogether, some debates over the merits of open science may be natural extensions of the disagreement and scandals that prompted open science proposals in the first place, while others may arise from uncertainty over the effectiveness of proposed solutions, or simply because open science practices represent a break from the status quo.

Addressing these controversies, and in particular the debates about the effect of open science practices on the social scientific literature, is beyond the scope of the present paper. Rather, we pose a question that logically precedes answers to those questions, specifically: how many social scientists are adopting open science practices, and what are the average perceptions of these practices in the social sciences? While some researchers are publicly starting to adopt open science practices (Christensen and Miguel 2018), there may be a lag between private adoption and public representation. For example, there are lags between pre-registration of a study or preparation of shareable code and article publication. Additionally, there are a small number of highly vocal scholars (including some authors of this article) who have expressed strong opinions either in support of or against the adoption of open science practices. However, these prominent voices may not be representative of the opinions of most scholars. Thus, there remains a considerable degree of uncertainty about researchers' current adoption of and attitudes toward open science practices (Anderson et al 2007).

Previous attempts to quantify adoption of open science practices tend to have small and largely unrepresentative convenience samples of survey respondents, and focus on just a single research discipline (e.g., van Assen, van Aert, and Wicherts 2015; Baker 2016; Buttliere 2014; Fuchs, Jenny, and Fiedler 2012). Researchers largely send solicitations to complete non-remunerated surveys to academic listserves, or to their personal networks via email or social media. In these surveys, scholars often claim to be more supportive of open science practices than their peers.

The present research, based on the State of Social Science (3S) Survey, generates a more robust estimate of the adoption of open science practices over time, and of general support and perceived norms of research transparency across four major social science disciplines: economics, political science, psychology and sociology. In addition, we connect the patterns in the data to theories regarding how institutions and technological innovations may affect the pace of scientific change (Romer 1990; Griliches 1957) and the development of new norms (Kuhn 1962, Hacking 1981).

Sample and Data

We solicited information using a monetarily incentivized survey from a representative sample of active, elite social science researchers in the fields of economics, political science, psychology, and sociology who work with empirical quantitative or qualitative data. The 3S survey queried respondents on awareness of, attitudes towards, perceived norms regarding, and adoption of open science practices. We randomly drew the sample from the complete set of authors who had published within a range of 3 years (2014-2016) in 10 of the most cited journals for each discipline. We also drew from the complete set of PhD Students enrolled in the top 20 North American departments in each discipline during the first half of 2018; see supplementary materials for details. We pre-registered analyses for our survey and posted our pre-analysis plan and study materials on the Open Science Framework. The present survey and descriptive analysis are the first part of a broader project described in the pre-analysis plan.

In total, we invited 6,221 individuals to complete a survey between April and August 2018 of whom 6,058 were contacted (emails did not bounce). Published Authors were compensated either $75 or $100 (randomly), and graduate students either $25 or $40 (response rates did not significantly vary by level of compensation). Arguably, our response rate represents an upper bound on the rate that is possible to achieve with a reasonable incentive strategy: at a median length of 15 minutes per survey, faculty were compensated at minimum $300 per hour.

Our incentive scheme achieved a completed survey response rate of 46.2%, implying that the study sample is broadly representative of active Published Authors and PhD Students in these four fields. Figure 1 presents the overall response rate of 46.2%, which ranged from 40% in Psychology to 55% in Political Science. We consistently obtained a majority of PhD Students, who responded at or above 50% in every field, while Published Authors (who had predominantly completed their doctoral training) responded at somewhat lower rates. Among respondents with North American email addresses, the response rates are slightly higher at 49% overall, 44% for Published Authors, and 53% for PhD Students.

As shown in Figure 1, the response rate for Published Authors from psychology journals is somewhat lower than that for the other disciplines' journals. This may be due to the fact that a subset of psychologists often publish with scholars or clinicians from other fields who are less active empirical researchers, and therefore may be less likely to respond to an invitation to complete a survey focused on research methods. Consistent with this explanation, the response rate from authors who published in clinical and neuroscience-focused journals is considerably lower than the rate for social and developmental psychology journals (see Appendix Figure 3 for survey response rates by journal). Similarly, the response rate for authors who had published in macroeconomics journals is somewhat lower than the rate from other economics journals, possibly due to the greater share of articles based on theoretical or simulation approaches, rather than quantitative empirical data analysis, in those journals.

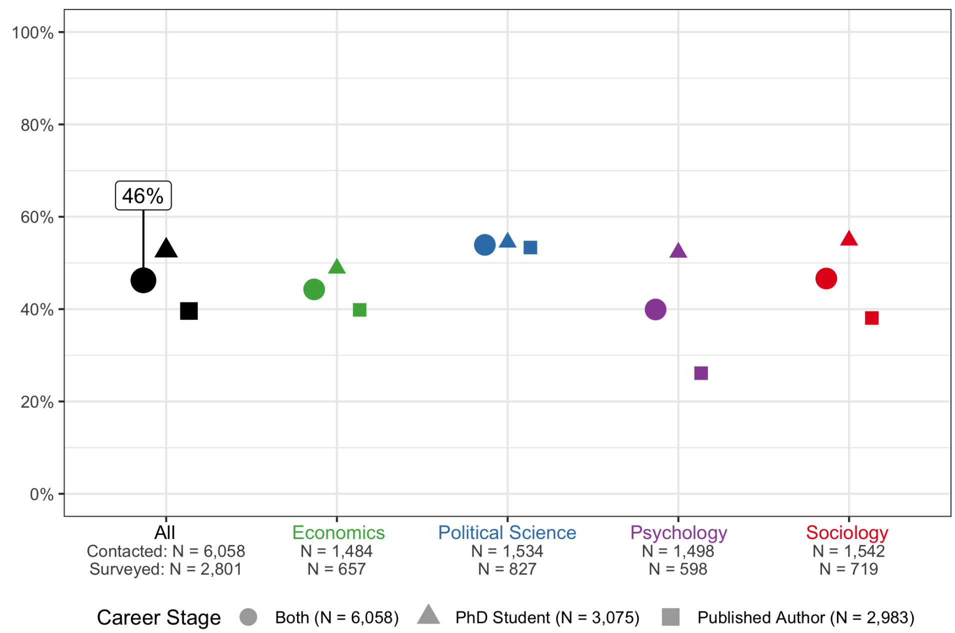

Figure 1: **Response Rates are High Across Disciplines.** Response rates by discipline and by career stage (PhD Student or Published Author). We contacted 6,058 researchers (6,221 researchers were invited via email but 163 emails bounced). Above figure consists of 2,787 respondents and 3,434 non-respondents, including 65 explicit opt-outs and 244 partially complete surveys, but excluding the 163 bounced emails.

Two concerns about the validity of our study design might remain. First, our survey results are entirely self-reported and one might be concerned that individuals could misstate their open science behavior, for example, due to surveyor demand effects. Second, even though to our knowledge the current sample is by far the largest and most representative attempt to assess open science attitudes and practices to date, one might still be concerned about the nature of selection into the sample. It remains possible that scholars who responded to the survey are non-randomly selected from the population along important dimensions. Indeed, we find that the response rate among Published Authors was significantly higher for those with more publications in leading disciplinary journals during the last three years, and for those at institutions in North America (see Appendix Table 13).

To better understand the degree to which non-random survey response may be a concern, we conducted an audit of open science behavior for a random sample of Published Author respondents and non-respondents from economics; economics was chosen because the vast majority of scholars use the same study registry and data posting platform, increasing the accuracy of the audit. We checked publicly available repositories and each author's website to determine whether they had previously pre-registered a study or posted data online; the details of the audit activity can be found in the SOM.

The audit activity yielded three main results. First, there is a high rate of agreement between self reports and actual behavior: despite only checking a limited number of online sources we were able to validate almost 80% of individuals' responses regarding adoption of open science practices (see Appendix Table 10). Second, while there is some selection into the sample, this appears to be primarily driven by scholars with a more empirical orientation being more likely to respond: response rates for theory-focused economists and macroeconomists are far lower than for other fields, at 27.2% for theory/macroeconomics/finance focused Published Authors versus 50.4% for the others, see Appendix Table 9). Third, scholars with a more empirical orientation do not appear to be selecting into our survey in a manner related to previous open science behavior (see Appendix Table 9). Taken together, these patterns suggest that the survey results are broadly representative of the behaviors and views of Published Authors with a more empirical orientation.

Retrospective Open Science Behavior

We first assess how the adoption of open science practices has changed over time, using survey respondents' self-reports and bounding them with a verification exercise (described below). We find that the last decade has been a time of rapid change across disciplines, with adoption of open science practices increasing dramatically.

Figure 2 presents the cumulative proportion of Published Authors who have adopted open science practices over time. We focus on scholars who received their PhD by 2009, as they had the opportunity to engage in these practices over much of the last decade (see Appendix Figure 4 for robustness to different PhD cutoff dates). 84% of Published Authors reported adopting an open science practice by 2017 (the last complete year for which we collected data), nearly doubling from 49% in 2010. The sharing of data, code and survey instruments show rapid increases starting after 2005, while the use of pre-registration has increased dramatically since 2013. Posting data or code online is the most common practice, followed by posting study instruments online, and then pre-registration. We also find in our survey data that those who reported adopting an open science practice at some point in the past are overwhelmingly likely to also have employed it in their most recent research project (see Appendix Table 14), indicating that scholars' adoption of these practices tends to be persistent.

The shaded areas underneath these lines adjust the adoption graph to incorporate the adoption rates of non-respondents, using the verified open science behavior for non-respondents found in our audit activity (see Appendix Table 10 for details on how these estimates are constructed). Even incorporating the likely behavior of non-respondents, we estimate that 76% of Published Authors have adopted an open science practice by 2017.

While there is an upward trend in all four disciplines, Figure 3 shows that adoption patterns differ across disciplines. The evolution of adoption in economics and political science appear relatively similar, with a rapid increase in the rates of posting data or code online. In economics, there has been a steady rise in posting study instruments online and pre-registration since around 2011. Political science has seen an increase in posting study instruments since 2005, and a steeper rise in pre-registration since 2014.

Psychology researchers were lagging behind economics and political science scholars until recently for all practices, but over the last few years psychology has had the most rapid increase in adoption. Psychologists also currently report the highest adoption rate for study pre-registration. Sociology has the lowest levels of adoption for all open science practices, but as with the other fields, there has been a steady increase in recent years.

Adoption rates of all three highlighted open science practices have been highest for researchers using experimental methods across social science disciplines, while adoption rates for posting study materials and pre-registration have been lower among researchers using non-experimental quantitative methods. Rates for all practices are the lowest among researchers using exclusively qualitative methods (Moravscik 2012), which likely helps to explain the lower adoption rates in sociology, where such methods are more common (see Figure 4).

As Figure 3 shows, the timing of increases in the reported adoption of transparent practices across disciplines coincides with notable developments in technology and institutional policy within and across disciplines. With respect to technology, online study registries and pre-registration plan registries seem to be accompanied by upward shifts in adoption. For example, the American Economic Association (AEA) registry was launched in April 2013, and in 2013, the Center for Open Science (COS) online archives allowed for pre-registration

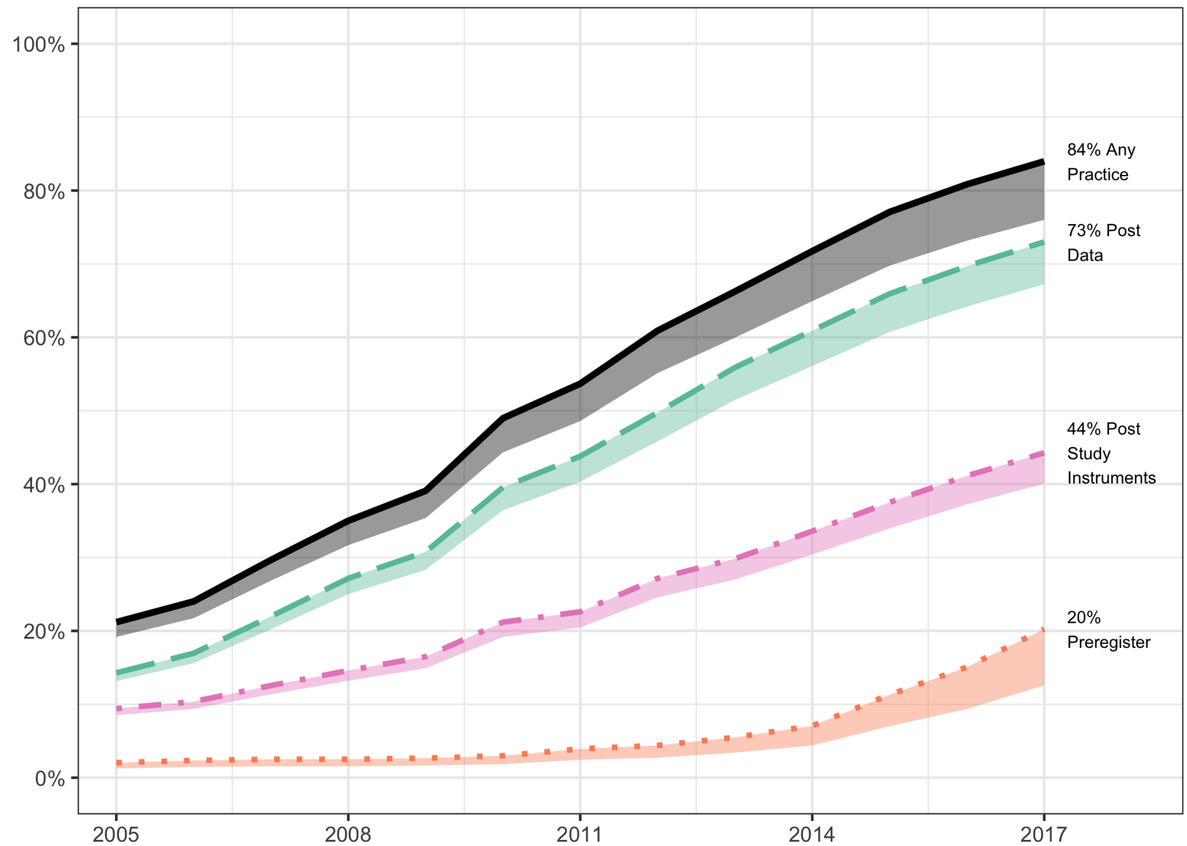

Figure 2: **Year of Adoption of Open Science Practices.** The chart shows for a given year the proportion of Published Authors who had first completed an open science practice in that year or previously. The solid black line shows the proportion of authors who had completed any open science practice by that year. The dashed green line shows the proportion of Published Authors who had posted data or code online by that year. The dash-dotted purple line shows the proportion of Published Authors who had posted study instruments online by that year. The dotted orange line shows the proportion of authors who had pre-registered an analysis or hypothesis by that year. Posting study instruments online is the response to the question “Approximately when was the first time you publicly posted study instruments online?”. Posting data or code online is the response to the question “Approximately when was the first time you publicly posted data or code online?”. Pre-registering hypotheses or analyses is the response to the question “Approximately when was the first time you pre-registered hypotheses or analyses in advance of a study?” The sample is restricted to Published Authors who completed their PhDs by 2009 (N = 637). The bottom of the shaded region is an estimated adoption rate for the entire sample contacted, including non-respondents; the methodology for calculating the adoption rate of non-respondents is outlined in Appendix Table 10.

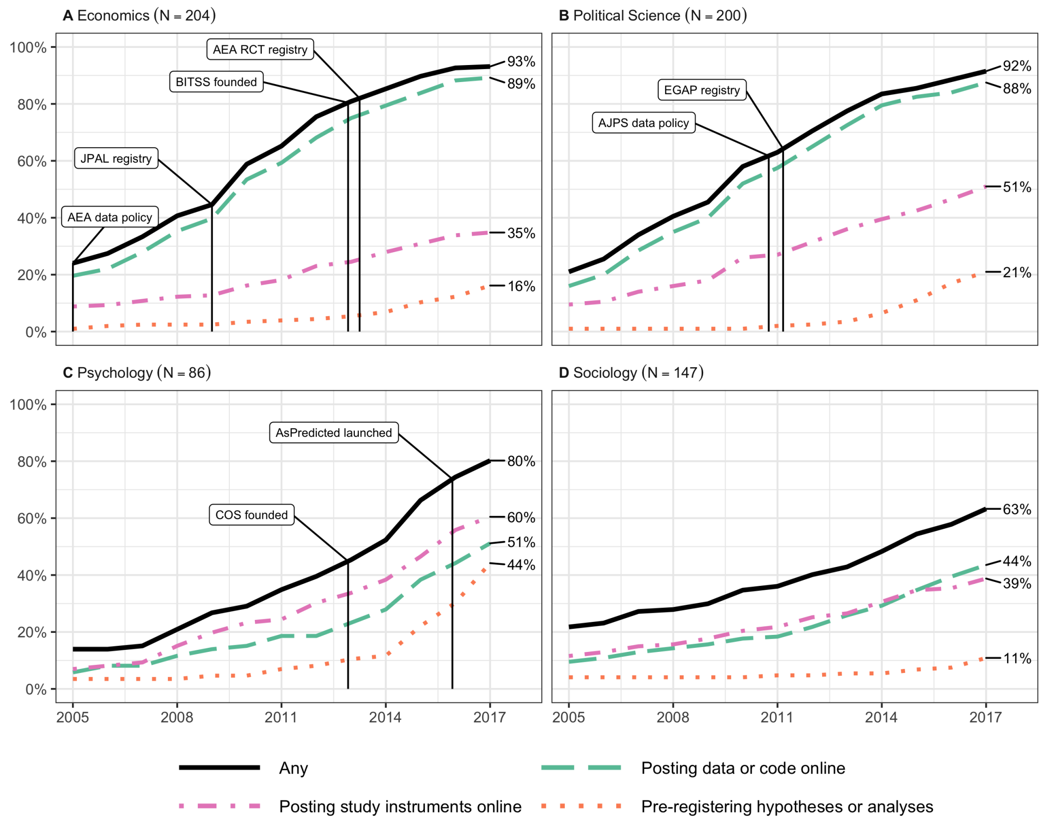

Figure 3: **Year of Adoption of Open Science Practices - by Discipline.** The chart shows for a given year the proportion of Published Authors who had first completed an open science practice in that year or previously, by discipline. The solid black line shows the proportion of authors who had completed any open science practice by that year. The dashed green line shows the proportion of Published Authors who had posted data or code online by that year. The dash-dotted purple line shows the proportion of Published Authors who had posted study instruments online by that year. The dotted orange line shows the proportion of authors who had pre-registered an analysis or hypothesis by that year. Posting study instruments online is the response to the question "Approximately when was the first time you publicly posted study instruments online?". Posting data or code online is the response to the question "Approximately when was the first time you publicly posted data or code online?". Pre-registering hypotheses or analyses is the response to the question "Approximately when was the first time you pre-registered hypotheses or analyses in advance of a study?". The sample is restricted to Published Authors who completed their PhDs by 2009. The abbreviated names of the organizations used in the labels represent the American Economic Association (AEA), the Abdul Latif Jameel Poverty Action Lab (JPAL), the Berkeley Initiative for Transparency in the Social Sciences (BITSS), the American Economic Association's registry for randomized controlled trials (AEA RCT), the American Journal of Political Science (AJPS), Evidence in Governance and Politics (EGAP), and the Center for Open Science (COS). The organizations mentioned in the figure are included in the panel of the discipline that they work in. BITSS and COS are interdisciplinary organizations, but are included with the discipline they are most associated with.

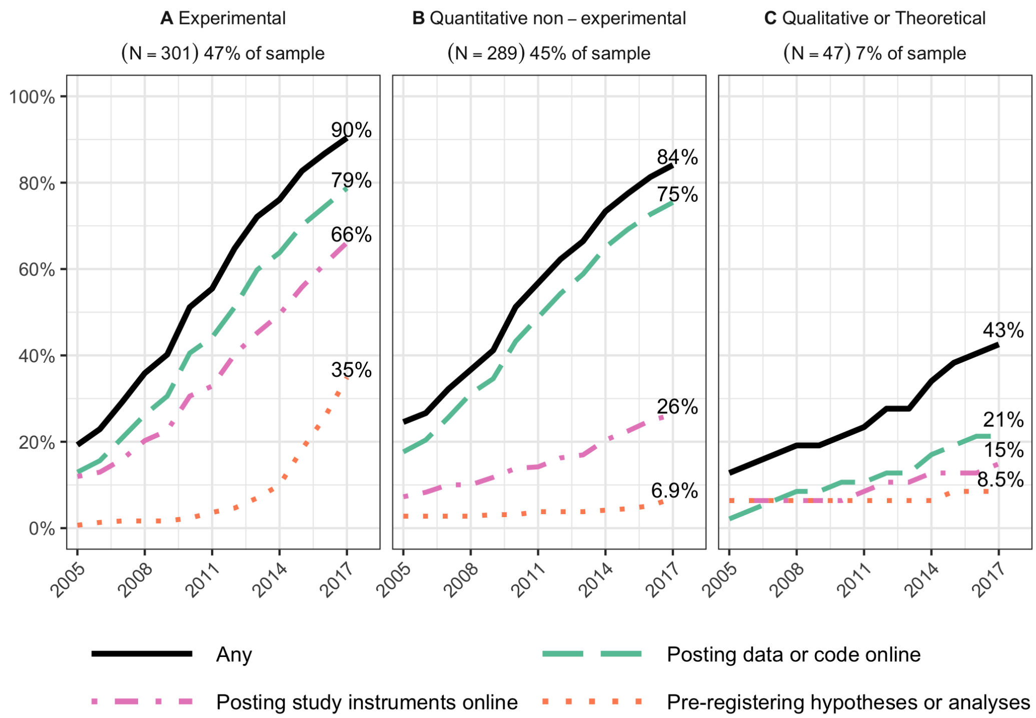

Figure 4: **Year of Adoption of Open Science Practices - By Research Focus.** The chart shows for a given year the proportion of Published Authors who had first completed an open science practice in that year or previously, categorized by the focus of their research. The classification is based on answers to the question "What methods do you use in your research? Please check all that apply." If a scholar only selected "Qualitative" or "Theoretical", they are classified as "Qualitative or Theoretical"; if they selected "Quantitative - Observational" or "Quantitative - Other" but not "Quantitative - Experimental", they are classified as "Quantitative non-experimental"; if they selected "Quantitative - Experimental", they are classified as "Experimental". The solid black line shows the proportion of authors who had completed any open science practice by that year. The dashed green line shows the proportion of Published Authors who had posted data or code online by that year. The dashed purple line shows the proportion of Published Authors who had posted study instruments online by that year. The dotted orange line shows the proportion of authors who had pre-registered an analysis or hypothesis by that year. Posting study instruments online is the response to the question "Approximately when was the first time you publicly posted study instruments online?". Posting data or code online is the response to the question "Approximately when was the first time you publicly posted data or code online?". Pre-registering hypotheses or analyses is the response to the question "Approximately when was the first time you pre-registered hypotheses or analyses in advance of a study?". The sample is restricted to Published Authors who completed their PhDs by 2009.

posting in economics, psychology and other social science fields. Institutionally, psychology journals began requiring data sharing and code or data posting quite recently, which could explain some of the more rapid trends in that field, whereas the AEA required data posting in 2005, which could partly explain why economics is the social science discipline with the earliest rise in adoption of data and code posting. The interdisciplinary organizations COS and Berkeley Initiative for Transparency in the Social Sciences (BITSS) (Miguel et al 2014) were founded in 2012, and have been homes for researchers working in all four social science disciplines. These developments in technology and institutions, along with the others labeled in Figure 3 as well as many others not mentioned in the figure, accord with theories of normal science and how occasional revolutions in scientific theory and practice take hold (Kuhn 1962, Hacking 1981).

Of course, there is also a role for bottom-up adoption rates in which students, faculty, and other researchers take up open science practices through processes of communication with peer networks. In 2012, some of the earliest economics articles using pre-analysis plans were published (Finkelstein et al 2012, Casey et al 2012), setting an example that many colleagues followed. It was in 2015, additionally, when a critical mass of blogs and Facebook groups addressed open science practices in psychology, and discussions about open science on Twitter gained momentum around 2016 (Singal, 2016; Huston, 2019). These bottom-up processes of change in attitudes and practices among scholars also likely played a role in driving the technological and institutional changes across disciplines noted above and in Figure 3.

While we are confident in our verification of a subset of respondents' reported adoption, and the resultant bounds we can place around our estimates of disciplinary and overall adoption trends, we acknowledge that reports were based on memory and thus may be imperfect. However, the fact that the slope of the adoption rates correspond to technological and institutional events provides some amount of confidence that they correspond to actual dates of adoption. Moreover, memories of first experiences (e.g., the first time posting data) are often better recalled than later instances (Rubin, Rahhal, & Poon, 1998).

Current Open Science Beliefs & Practices

The data indicate that open science practices are on the rise across four major social science fields, but how supportive of research transparency are scholars today? How much are they currently planning to engage in open science practices? Figure 5 suggests that awareness levels of and support for open science practices are high across all four disciplines. Scholars are generally aware of open science practices (for instance, respondents were asked "Have you ever heard of the practice of publicly posting data and code online for a completed study?"), and they are favorably inclined toward them (e.g., "To what extent do you believe that publicly posting data or code online is important for progress in [Discipline]?"). There is not much of a difference between disciplines, apart from sociology researchers having a somewhat lower level of awareness, support, and adoption. Patterns are similar across specific open science practices (see Appendix Tables 15 - 22).

Although comparison across opinion scales and adoption rates is challenging, it appears that actual rates of adoption of open science practices may currently lag behind stated support. It is notable that there are fairly high levels of stated support for open science even among scholars in a discipline like sociology where these tools are not (yet) widely used or taught and where there is a relative lack of institutionalization of these practices.

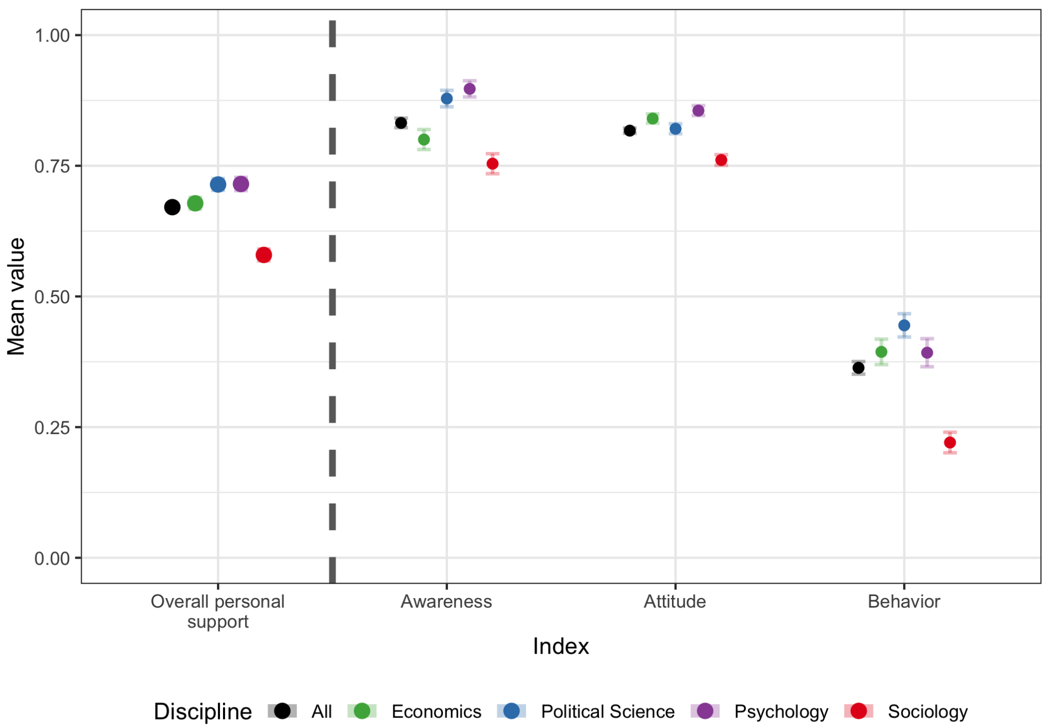

Figure 5: **Open Science Awareness, Attitudes and Behavior - by Discipline.** Lines around the dots are 95% confidence intervals for the estimates. Awareness is an index comprised of questions related to the respondent's i) Awareness of posting data and code online, ii) Awareness of posting study instruments and iii) Awareness of pre-registration. Behavior is an index comprised of questions related to the respondent's i) Behavior of posting data and code online, ii) Behavior of posting study instruments and iii) Behavior of pre-registration. Attitudes is an index comprised of questions related to the respondent's i) Attitudes of posting data and code online, ii) Attitudes of posting study instruments and iii) Attitudes of pre-registration. Overall Personal Support is an average of the three indices. The questions and methodology that are used to construct the indices can be found in Appendix Table 7.

Perhaps surprisingly, Published Authors and PhD students show similar levels of awareness of and support for open science practices as shown in Appendix Figures 6 and 7 respectively. This is in contrast to the authors' prior expectation that PhD Students would exhibit a more supportive attitude toward open science, and suggests that PhD Students may not be the vanguard of changing practices. Open science practices are actually higher among

Published Authors, though this is likely because many PhD Students—especially those in their first few years, when they are taking coursework—have not yet had the opportunity to apply the practices to their own work. Researchers across disciplines who use experimental methods show the highest levels of awareness, support, and practice, followed by researchers who use non-experimental quantitative methods. Although qualitative researchers show the least awareness, support, and practice, their awareness and stated support are still at relatively high levels as shown in Appendix Figure 8.

Perceived norms

How do social scientists perceive their fields today, in terms of support for and adoption of open science practices? We measured respondents' perceptions of norms in their disciplines, and compared these perceptions of field-wide opinion and behavior to the average opinion and behavior reported directly in the survey. To measure norms of opinion, we asked respondents to estimate how supportive others in their field are of (1) posting code and data online, and (2) pre-registering hypotheses or analyses in advance of a study. Respondents estimated the percentage of people in their field who fall into each of five opinion categories, ranging from "Not at all in favor" to "Very much in favor," using a dynamic histogram (see Appendix Figure 10). To measure norms of behavior, we asked respondents to estimate what percentage of researchers in their field actually engage in each of these practices.

Figure 6 depicts scholars' perceptions of their field, in terms of the distribution of opinion about and adoption rates of the two open science practices, against the actual distribution of opinion and adoption rates as reported by survey respondents in their field. Two findings are apparent. First, perception of support, in green, is consistently smaller than actual support—by a substantial amount when considering attitudes toward posting data or code online. Second, perception of opposition toward open science practices is much greater than actual (survey-estimated) opposition, particularly for the case of attitudes toward pre-registration. (Respondents substantially overestimated the proportion of scholars who are indifferent toward posting data or code online, as well).

A second finding depicted in Figure 6 is that survey-estimated rates of support for both open-science practices is substantially larger than the rates of actual behavior–particularly when taking into account respondents who said they were either "Very much" and "moderately" in favor of the practice. This pattern is consistent with substantial latent support for adoption of these practices in the four social sciences that may contribute to further rises in adoption rates in future.

While the rates of adoption demonstrated by our previous measures may or may not have seemed surprising to readers, these data show that the high adoption rate of open science practices would be surprising to our survey respondents, who appear to significantly underestimate open science adoption and support.

There are various possible explanations for why respondents appear to be more in favor of data posting and pre-registration than they believe others in their field to be. One immediate possibility is that our survey sample is selected and unrepresentative in important ways. For instance, we selected respondents based on their publication history in leading research journals and among the most highly-ranked PhD programs, and these populations are not representative of the entire discipline about which respondents are making estimates. Of course, this subgroup of "elite" scholars may be particularly influential in driving the change of social norms in the discipline. Moreover, those who chose to respond to our survey invitation may be more supportive of open science than non-respondents, further shifting sample means, although the evidence we presented above from the audit activity

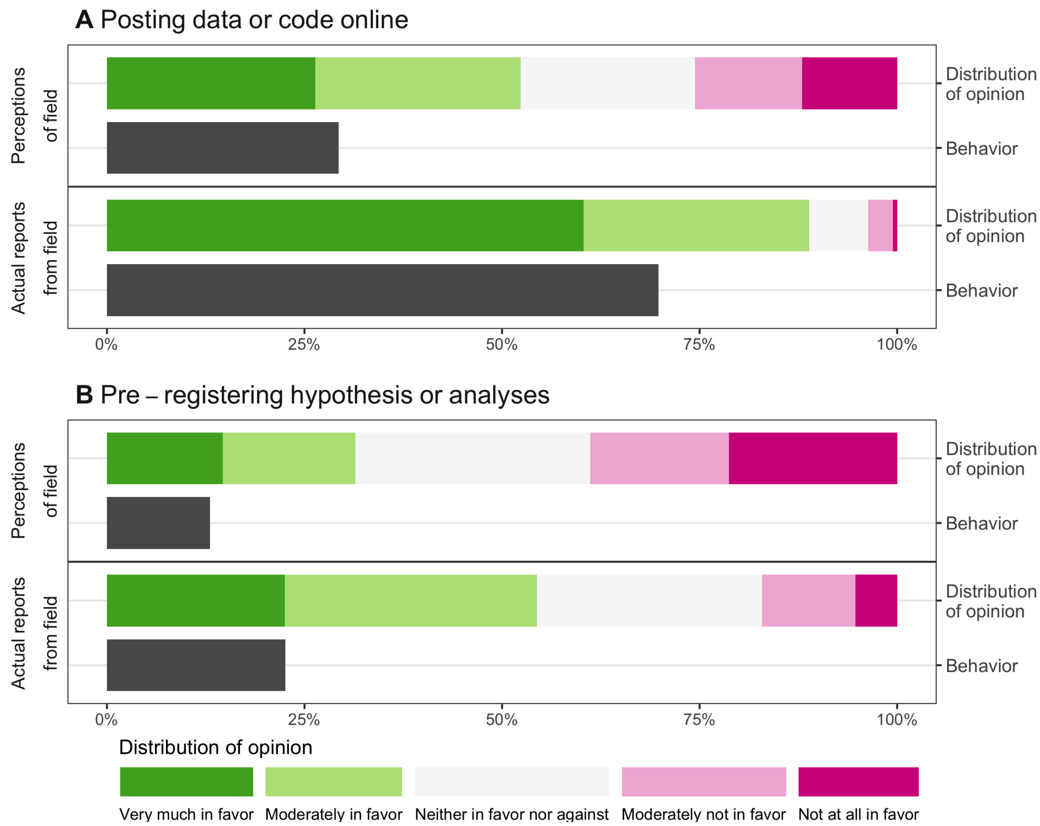

Figure 6: **Perceived and Actual Support for Open Science among Published Authors.** The chart shows differences between perceived and actual support for two practices: posting data or code online and pre-registering hypotheses or analyses. The sample is restricted to Published Authors; the analogous data for Ph.D. students are presented in Appendix Figure 9. Within each panel, the first bar shows the perceived distribution of support for the practice among Published Authors. This is constructed by asking individuals what percentage of researchers in their field they believe fall into each opinion category, and then averaging over their responses. The solid black bar below shows the fraction of researchers in their field they believe have done the practice. The third bar in the panel shows the distribution of support for the practice constructed using the responses elicited from the Published Authors that we sampled. The final solid black bar shows the proportion of researchers who have actually done the stated practices, using the responses elicited from our survey. Colors indicate the level of support, with green indicating more and red indicating less support. Adjusting the behavior figures to account for non-respondents (using the same methodology as in Figure 2) we find that the adjusted share of Published Authors posting data is 64.3% and the adjusted share of Published Author's posting pre-analysis plans is 14%.

suggests this is less likely.

Another explanation is that respondents are over-reporting their support for open science for reasons of self or social image. However, admitting some social desirability toward responding favorably about open science in an anonymous survey seems to support the idea that a relatively strong social norm in favor of open science has already developed, as suggested in the rates of "actual reports from the field" in Figure 6. The figure shows that the median respondent is in favor of these practices. This interpretation suggests a social norm in favor of open science at work, even if practices lag behind the ideal. Similarly, the social science research community could be in a period of rapid methodological change, in which case we might expect that beliefs about practices could be temporarily out of sync with actual behaviors. For instance, scholars' views about the state of open science in their discipline could be shaped by their own experiences during their graduate training, or based in part on current journal publications, but both would only capture actual attitudes and practices in the field with a lag.

This set of analyses is consistent with the idea of a current cultural shift in social science research communities, in which behaviors and attitudes are already changing and community members are partially attuned to the change.

Discussion

Data from a recent representative survey of scholars in four large social science disciplines – economics, political science, psychology, and sociology – indicates that the adoption of open science practices has been increasing rapidly over the past decade. Behaviors such as posting data and materials that were nearly unknown in some fields as recently as 2005 are now practiced by the majority of scholars. Other newer practices, such as study pre-registration, have experienced a sharp rise in adoption just in recent years, especially among scholars who engage in experimental research. While trends are similar to other fields, overall levels of adoption are lowest in sociology. Contrary to our expectations, there is no clear evidence of a generational shift, or of an old guard standing in the way of change: attitudes towards open science practices are remarkably similar among both PhD Students and more established Published Authors. The high levels of support for open science practices expressed among our respondents indicates that the classic scientific ethos famously described by Merton (1942) is alive among today's social scientists. A data validation activity confirms that self-reported behaviors are strongly related to actual behavior, and that the selection of survey respondents into the sample has not produced misleading results.

The second main finding of the analysis is that stated support for open science practices is outpacing both their actual adoption and respondents' beliefs about others' support. Taken together, this pattern suggests that social science research communities are in a period of rapid transformation in terms of their research practices, a shift that is not yet entirely appreciated by the community. To follow this co-evolution of behavioral adoption, awareness, and support for open science practices, we plan to collect additional rounds of the 3S survey in the future. These representative snapshots of open science adoption and perception, we argue, can describe the state of the social sciences from the perspective of whether they are currently in the type of transition state described by historians of science as a shift out of "normal" science into one of crisis and eventual transformation (Kuhn 1962, Hacking 1981).

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Supplementary Materials

Materials and Methods

Sample

Our population consists of scholars at two career stages.

Published Authors:

These are active social science researchers who have published in a top-10 leading journal within their discipline. We use the following definitions:

- *Active:* At least one publication in 2014-2016.
- *Top-10 leading journals:* The selection of journals was based on citation impact factor. We also added the respective version of the Annual Review for each discipline. In total we have 45 journals, shown in Appendix Tables 2 through 5.
- *Discipline:* Before a participant entered the survey, we took an initial guess of their discipline. For PhD Students it was their department, for Published Authors the discipline they have published in most frequently during 2010-2016, with ties split by the most recent publication. We used the initial guess to draw our sample, and for the analysis. The exception was the following, which occurred in a small number of cases: at the beginning of the survey we ask each participant for their primary discipline. If their answer did not match with the initial guess, and they indicated that they do not feel familiar enough to comment on the initially guessed discipline, we asked them to choose which of the four disciplines they feel sufficiently familiar with. We assigned this discipline to them for our analysis. If they did not feel familiar enough with any of our four disciplines, the survey ended, and they did not

become part of our analysis sample.

PhD Students:

These are current PhD Students from top-20 North American doctoral programs within each discipline. We use the following definitions:

- *Current:* Listed on departmental websites in Fall 2017.
- *Top-20 North American Universities:* The 20 US and Canadian universities with the highest rank according to the Times Higher Education World University Rankings 2017. The complete list of schools used can be seen in Appendix Table 6.

PhD Students who are also Published Authors were sampled only as PhD Students.

Participation Incentives:

Achieving a high response rate and sample size was a critical issue for the validity of our study. Several previous surveys on related transparency and reproducibility topics featured minimal or no monetary compensation for participants and had fairly low response rates, most in the range of 10 to 24% (see Baker (2016); John, Loewenstein, and Prelec (2012)). We seek to generate longitudinal data on a far more representative population of leading social science researchers by offering much higher levels of compensation.

Participants were randomly offered either a standard or high incentive. The levels differ between Published Authors and PhD Students, and are based on the response rates from our pilot.

Initial contact was made via email. There were three reminders at intervals following the initial email contact. The survey was administered using a customized online tool (a custom-built interface on top of Qualtrics). Appendix Table 1 shows the monetary value of the incentives used in the survey. PhD students offered the High incentive had an 8.2 percentage point higher response rate and Published Authors offered the High incentive had a 0.8 percentage point higher response rate.

Appendix Table 1: Participation Incentives

Career Stage	**Standard (80% of sample)**	**High (20% of sample)**
Published Authors	$75	$100
PhD Students	$25	$40

Descriptive Analysis:

We aggregate individual survey questions into five measures (awareness, behavior, attitudes, descriptive norms, and prescriptive norms) for each of the three practices (posting data and code online, posting study instruments, and pre-registration). Details of the aggregation method are described in Appendix Table 8.

We also measure trustworthiness of the literature, behavioral intentions, and projected norms through a set of questions.

We then aggregate the large number of measures to a smaller number of sub-indices and broad indices. Each sub-index is a simple average of measures, and each broad-index is a simple average of sub-indices. See Appendix Table 7 and Appendix Table 8 for details.

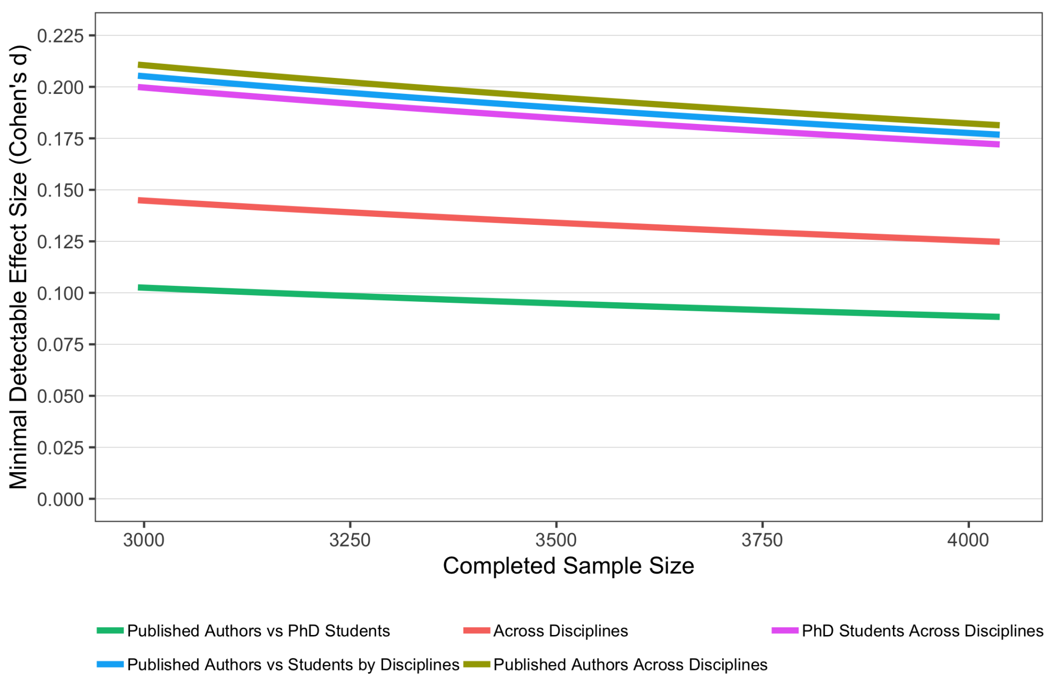
Altogether, our outcome variables for the descriptive analysis are:

- Sub-Indices: Awareness, Behavior, Attitudes, Descriptive Norms, Prescriptive Norms, Posting data and code online, Posting study instruments, Pre-registration
- Broad Indices: Personal support for open science, Norms, Overall open science, Trustworthiness of literature

The mappings from questions to sub-indices, and from sub-indices to broad-indices can be found in Appendix Tables 7 through 8.

Power Calculations:

We based power calculations on conservative estimates of response rates from prior transparency surveys and our own pilot. We conducted power calculations expecting roughly equal numbers in each discipline. These assumptions yield an expected final sample size between 3,000 to 4,000, with N=3200 as our best guess. As shown in the Appendix Figure 1, with a power threshold of 80%, we are able to detect small differences in means across groups.



Appendix Figure 1: **Power Calculations.** The chart shows the minimum detectable effect size at different sample sizes for comparing different subgroups. Power calculations were preregistered. The figure shows the power calculations that we pre-registered. Our realized sample size was 2801. At this sample size, the minimum detectable effect by author type is 0.106, the minimum detectable effect by discipline is 0.1497 and the minimum detectable effect for the interaction is 0.212.

Regression Specifications:

For each outcome variable described in the previous sub-section, we run the following linear regressions.

First, an analysis of differences across disciplines (dropping subscripts denoting individual participants).

$$y = \alpha_1 + \beta_{1a} * \mathbb{I}\{Econ\} + \beta_{1b} * \mathbb{I}\{PoliSci\} + \beta_{1c} * \mathbb{I}\{Psych\} + u_1$$

Second, an analysis of differences between Published Authors and PhD Students.

$$y = \alpha_1 + \beta_2 * \mathbb{I}\{PublishedAuthor\} + u_2$$

Third, an analysis that examines both of these dimensions of heterogeneity:

$$\begin{aligned} y = \alpha_1 + \beta_{3a} * \mathbb{I}\{Econ\} + \beta_{3b} * \mathbb{I}\{PoliSci\} + \beta_{3c} * \mathbb{I}\{Psych\} + \beta_{3d} * \mathbb{I}\{PublishedAuthor\} \\ + \beta_{3e} * \mathbb{I}\{Econ\} * \mathbb{I}\{PublishedAuthor\} + \beta_{3f} * \mathbb{I}\{PoliSci\} * \mathbb{I}\{PublishedAuthor\} \\ + \beta_{3g} * \mathbb{I}\{Psych\} * \mathbb{I}\{PublishedAuthor\} + u_3 \end{aligned}$$

We employ a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). We carry out FDR adjustment across the primary outcome variables.

We also present the averages of our outcome variables by discipline and career stage graphically and estimate regression specifications adjusted for covariates (age, gender, tenured status, US department, leadership position).

Validation Exercise:

In order to validate our survey responses and check for balance across respondents and non-respondents, we conducted an audit of our economics Published Authors. Specifically, we randomly sampled i) 300 economics Published Authors who completed our survey and ii) 100 economics Published Authors who were contacted but did not complete our survey.

We then conducted two audit activities. For *all* sampled individuals we conducted an audit of these authors' pre-registration and data posting behaviors using publicly available information. The protocol for this activity is the first subsection below. This audit activity was completed between March 15, 2019 and March 29, 2019.

The second audit activity was conducted only for the non-respondent sample, and was completed between April 4, 2019 and April 15, 2019. In this activity, we used publicly available data sources to collect data on the primary subfield of these non-respondents. The protocol for this activity is below.

After these subfields were collected we manually categorised these subfields into one of three categories. The first of these was "Theory focused", which is categorised as any individual who listed Microeconomic Theory or Econometrics as a primary subfield. The second was "Macroeconomics/Finance", which was any author who listed Macroeconomics or Finance as a primary field. Finally, all other authors were categorised in the residual category.

Audit Protocol - Open Science behaviors

The goal of the audit is to identify whether a Published Author in the selected sample has (i) pre-registered an analysis or (ii) posted data or code for their projects. We use an author's last name as a keyword to search a set of popular open science websites used by economics scholars.

General Procedure Since the collection of last names was fully automated, auditors first verify whether an author's last name corresponds to a Published Author by looking for a university affiliation using a Google search.

The auditors then go to the websites listed below, and search by last name only. They look through the search results and try to identify the Published Author using their first name or affiliation. Then, following the link associated with an identified author, auditors look for a (i) pre-analysis plan or (ii) posted data or code on the websites. As soon as a match is found, auditors stop searching and record the match and a link to the matched page. If no match can be found, the auditors record that no match was found.

Websites for posting data or code online

- Dataverse.org
- Authors' personal websites

Websites for pre-registering analysis (PAP)

- SocialScienceRegistry.org (AEA RCT registry). Details of some pre-analysis plans may not be visible to the public, but we still count those as having pre-registered.
- OSF.io
- Authors' personal websites

Audit Protocol - Author Subfield

The goal of this activity is to collect data on the primary subfields of Economics Published Authors that did not complete the survey. The following steps are followed to complete this activity:

- Go to the author's webpage. Record subfields information if subfields of interest are listed on the homepage or another part of the webpage.
- Open the author's CV. Record any subfields that are listed on the author's CV.

Sampling frame and Outcome Index Construction:

Appendix Table 2: Economics Journals

Index	**Journal**	**Publisher**
NR	Annual Review of Economics	Annual Reviews
1	The Quarterly Journal of Economics	Oxford University Press
2	Journal of Political Economy	University of Chicago Press, JSTOR
3	American Economic Review	American Economic Association, JSTOR
4	Econometrica	Wiley, JSTOR
5	Journal of Economic Growth	Springer, JSTOR
6	Review of Economic Studies	Oxford University Press
7	Journal of Monetary Economics	Elsevier
8	Journal of Econometrics	Elsevier
9	Journal of Labor Economics	University of Chicago Press
10	The Review of Economics and Statistics	MIT Press

Sampling Frame Economics Published Authors Journals used to sample economics Published Authors. While the Annual Review of Economics is not ranked, it is included as it is an influential journal for the field. The selection of journals is based on citation impact factor.

Appendix Table 3: Political Science Journals

Index	**Journal**	**Publisher**
NR	Annual Review of Political Science	Annual Reviews
1	American Journal of Political Science	Wiley
2	American Political Science Review	Cambridge University Press
3	The Journal of Politics	University of Chicago Press
4	British Journal of Political Science	Cambridge University Press
5	Political Analysis	Oxford University Press
6	Comparative Political Studies	SAGE Publishing
7	World Politics	Cambridge University Press
8	Political Behavior	Springer
9	International Organization	Cambridge University Press
10	International Studies Quarterly	Wiley

Sampling Frame Political Science Published Authors Journals used to sample political science Published Authors. While the Annual Review of Political Science is not ranked, it is included as it is an influential journal for the field. The selection of journals is based on citation impact factor.

Appendix Table 4: Psychology Journals

Index	**Journal**	**Publisher**
NR	Annual Review of Psychology	Annual Reviews
1	Psychological Science	SAGE Publishing
2	Psychological Bulletin	American Psychological Association
3	American Psychologist	American Psychological Association
4	Journal of Experimental Psychology - General	American Psychological Association
5	Trends in Cognitive Sciences	Elsevier
6	Social Cognitive and Affective Neuroscience	Oxford University Press
7	Journal of Personality and Social Psychology	American Psychological Association
8	Journal of Consulting and Clinical Psychology	American Psychological Association
9	Child Development	Wiley
10	Developmental Psychology	American Psychological Association

Sampling Frame Psychology Published Authors Journals used to sample psychology Published Authors. While the Annual Review of Psychology is not ranked, it is included as it is an influential journal for the field. The selection of journals is based on citation impact factor.

Appendix Table 5: Sociology Journals

Index	Journal	Publisher
NR	Annual Review of Sociology	Annual Reviews
1	American Sociological Review	SAGE Publishing
2	American Journal of Sociology	University of Chicago Press
3	European Sociological Review	Oxford University Press
4	Social Forces	Oxford University Press
5	Social Problems	Oxford University Press
6	Demography	Springer
7	Criminology	Wiley
8	Gender & Society	SAGE Publishing
9	Administrative Science Quarterly	SAGE Publishing
10	Sociology of Education	SAGE Publishing
11	Social Networks	Elsevier

Sampling Frame Sociology Published Authors Journals used to sample sociology Published Authors. While the Annual Review of Sociology is not ranked, it is included as it is an influential journal for the field. The selection of journals is based on citation impact factor and disciplinary expert recommendation.

Appendix Table 6: Top 20 North American Doctoral Programs

Rank	**University**	**Country**
1	Stanford University	US
2	Yale University	US
3	University of Chicago	US
4	Harvard University	US
5	Massachusetts Institute of Technology	US
6	University of Michigan-Ann Arbor	US
7	Princeton University	US
8	University of California, Los Angeles	US
9	University of California, Berkeley	US
10	Columbia University	US
11	University of Pennsylvania	US
12	Cornell University	US
13	Duke University	US
14	University of Wisconsin-Madison	US
15	University of Toronto	Canada
16	University of British Columbia	Canada
17	New York University	US
18	Northwestern University	US
19	University of Washington-Seattle	US
20	University of California, San Diego	US

Sampling Frame PhD Students PhD Students in the paper were sampled from universities listed in the table. The ranking is the Times Higher Education 2017 Social Science ranking.

Appendix Table 7: Mapping Measures to Indices

Measure	**Sub-Index**	**Broad Index**
1.1.1 Awareness of posting data and code online	1.1 Awareness	1. Personal support for open science
1.1.2 Awareness of posting study instruments		
1.1.3 Awareness of pre-registration		
1.2.1 Behavior of posting data and code online	1.2 Behavior	
1.2.2 Behavior of posting study instruments		
1.2.3 Behavior of pre-registration		
1.3.1 Attitudes of posting data and code online	1.3 Attitudes	
1.3.2 Attitudes of posting study instruments		
1.3.3 Attitudes of pre-registration		
2.1.1 Descriptive norms of posting data and code online	2.1 Descriptive norms	2. Norms
2.1.2 Descriptive norms of pre-registration		
2.2.1 Prescriptive norms of posting data and code online	2.2 Prescriptive norms	
2.2.2 Prescriptive norms of pre-registration		
3.1.1 Awareness of posting data and code online	3.1 Posting data and code online	3. Overall Open Science
3.1.2 Behavior of posting data and code online		
3.1.3 Attitudes of posting data and code online		
3.1.4 Descriptive norms of posting data and code online		
3.1.5 Prescriptive norms of posting data and code online		
3.2.1 Awareness of posting study instruments	3.2 Posting study instruments	
3.2.2 Behavior of posting study instruments		
3.2.3 Attitudes of posting study instruments		
3.3.1 Awareness of pre-registration	3.3 Pre-registration	
3.3.2 Behavior of pre-registration		
3.3.3 Attitudes of pre-registration		
3.3.4 Descriptive norms of pre-registration		
3.3.5 Prescriptive norms of pre-registration		
4. Trustworthiness of literature		4. Trustworthiness of literature

Measures incorporated in Indices The table shows the mapping from measures (see Appendix Table 8) to indices. Each sub-index is a simple average of measures, and each broad-index is a simple average of sub-indices.

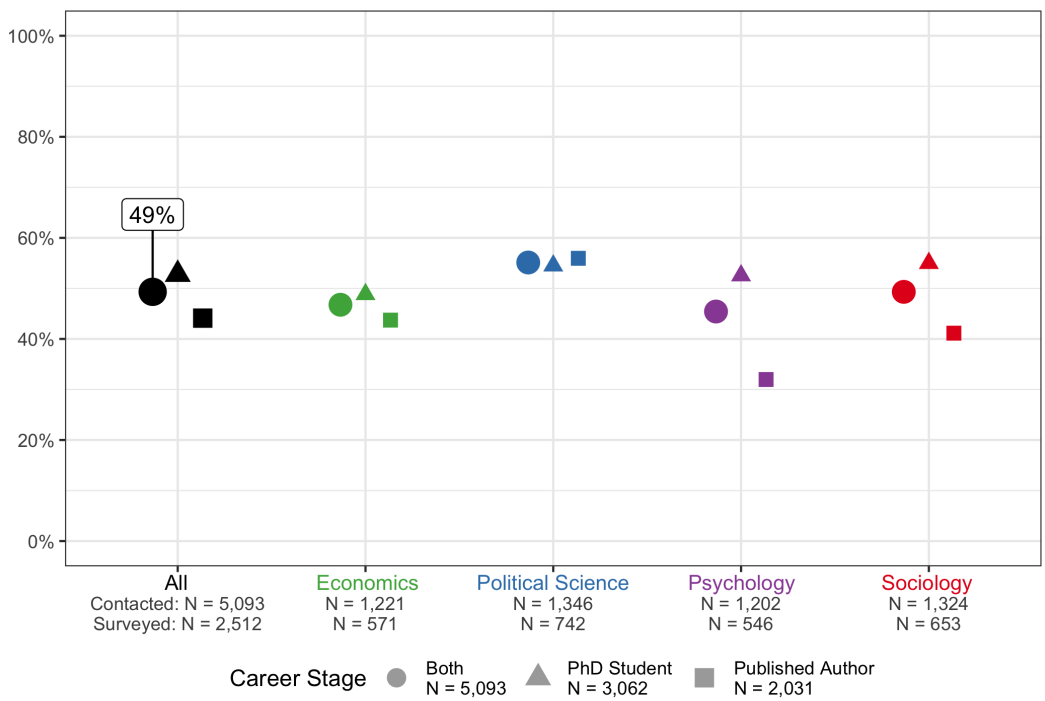
Appendix Table 8: Mapping Measures to Indices

Question	Measure	Rescaling and Aggregation
Have you ever heard of the practice of publicly posting data and code online for a completed study?	1.1.1 Awareness of posting data and code online	”No” → 0, ”Yes” → 1
Approximately how many times have you publicly posted data or code online?	1.2.1 Behavior of posting data and code online	Question “Approximately. . . ” coded as 0 → 0, anything ≥ 1 → 1 Question “Think about the last. . . ” coded as “No” → 0, “Yes” → 1, “I have not published an empirical paper” → NA Question ”Do you encourage . . . ” coded as (“No, and I don’t plan to”, “No, but I plan to in the future”) → “0”, (“Yes, I do”) → “1” Average over questions
Think about the last empirical paper you published. Have you publicly posted the data or code online for that paper?		
Do you encourage students to publicly post data or code online?		
To what extent do you believe that publicly posting data or code online is important for progress in [Discipline]?	1.3.1 Attitude of posting data and code online	Rescale from 1-5 to 0-1 Average over questions
What is your opinion of publicly posting data or code online?		
In your estimation, what percentage of researchers across the discipline of [Discipline] publicly post data or code online?	2.1.1 Descriptive norm of posting data or code online	Average over questions
In your estimation, what percentage of researchers in your sub-field of [Sub-discipline] publicly post data or code online?		
In your estimation, what is the distribution of opinion across the discipline of [Discipline] about publicly posting data or code online?	2.2.1 Prescriptive norm of posting data or code online	Calculate mean of distribution Rescale from 1-5 to 0-1
In your estimation, what is the distribution of opinion in your sub-field of [Sub-discipline] about publicly posting data or code online?		
Have you ever heard of the practice of publicly posting study instruments online for a completed study?	1.1.2 Awareness of posting study instruments	”No” → 0, ”Yes” → 1
Approximately how many times have you publicly posted study instruments online?	1.2.2 Behavior of posting study instruments	Question “Approximately. . . ” coded as 0 → 0, anything ≥ 1 → 1 Question “Think about the last. . . ” coded as “No” → 0, “Yes” → 1, “I have not published an empirical paper” → NA Question ”Do you encourage . . . ” coded as (“No, and I don’t plan to”, “No, but I plan to in the future”) → “0”, (“Yes, I do”) → ”1” Average over questions
Think about the last empirical paper you published. Have you publicly posted the study instruments online for that paper?		
Do you encourage students to publicly post study instruments online?		
To what extent do you believe that publicly posting study instruments online is important for progress in [Discipline]?	1.3.2 Attitude of posting study instruments	Rescale from 1-5 to 0-1 Average over questions
What is your opinion of publicly posting study instruments online?		
Have you ever heard of the practice of pre-registering hypotheses or analyses in advance of a study?	1.1.3 Awareness of pre-registration	Rescale from 1-5 to 0-1 Average over questions

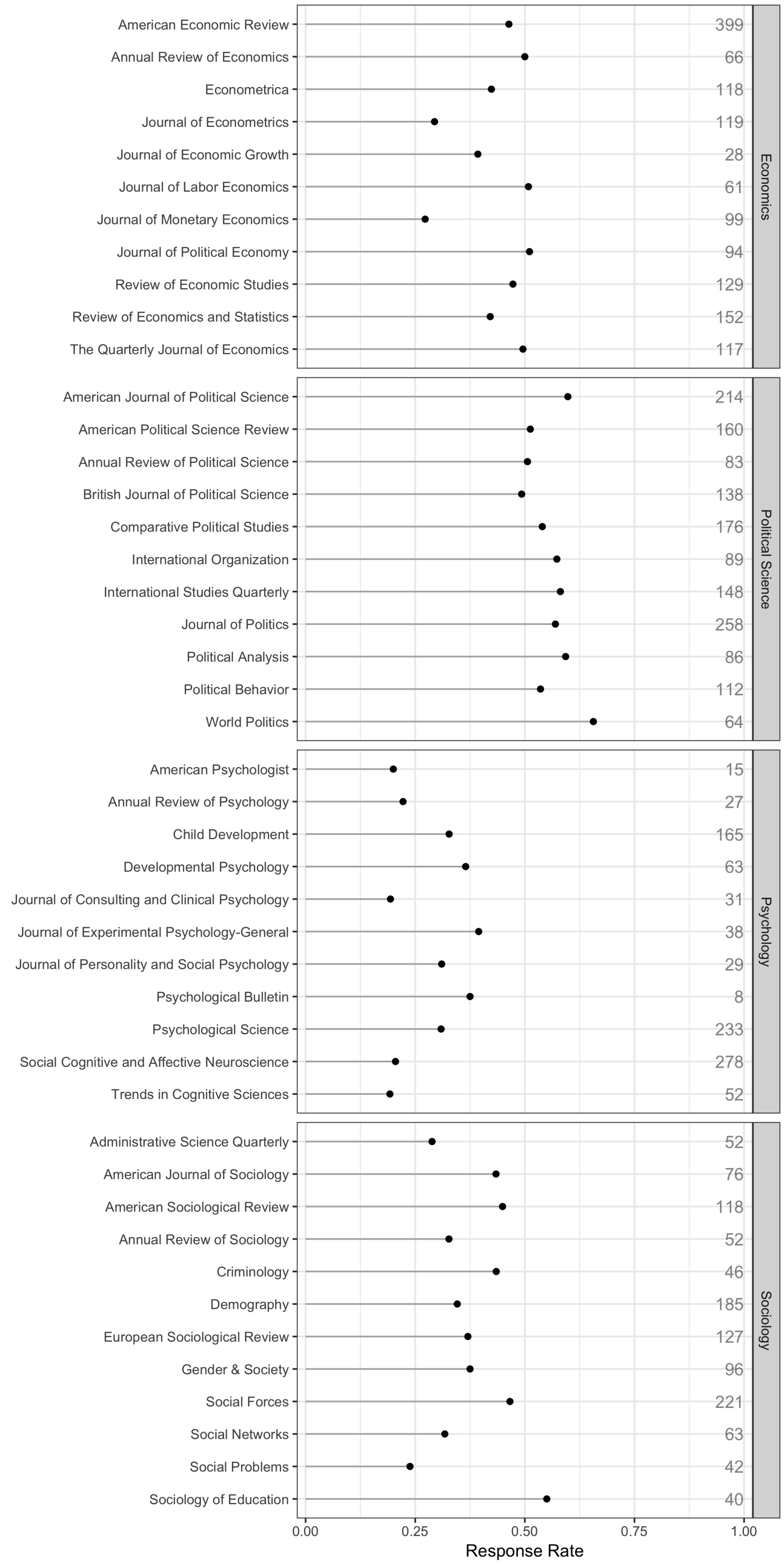
Approximately how many times have you pre-registered hypotheses or analyses in advance of a study?	1.2.3 Behavior of pre-registration	Question “Approximately. . . ” coded as 0 → 0, anything ≥ 1 → 1 Question “Think about the last. . . ” coded as “No” → 0, “Yes” → 1, “I have not published an empirical paper” → NA Question ”Do you encourage . . . ” coded as (“No, and I don’t plan to”, “No, but I plan to in the future”) → “0”, (“Yes, I do”) → ”1” Average over questions
Think about the last empirical research you completed. Did you pre-register the hypotheses or analyses for that research?		
Do you encourage students to pre-register hypotheses or analyses in advance of a study?		
To what extent do you believe that pre-registering hypotheses or analyses is important for progress in [Discipline]?	1.3.3 Attitude of pre-registration	Rescale from 1-5 to 0-1 Average over questions
What is your opinion of pre-registering hypotheses or analyses?		
In your estimation, what percentage of researchers across the discipline of [Discipline] pre-register hypotheses or analyses in advance of a study?	2.1.2 Descriptive norm of pre-registration	Rescale from 0-100 to 0-1 Average over questions
In your estimation, what percentage of researchers in your sub-field of [Sub-discipline] pre-register hypotheses or analyses in advance of a study?		
In your estimation, what is the distribution of opinion across the discipline of [Discipline] about pre-registering hypotheses or analyses in advance of a study?	2.2.2 Prescriptive norm of pre-registration	Calculate mean of distribution Rescale from 1-5 to 0-1
In your estimation, what is the distribution of opinion in your sub-field of [Sub-discipline] about pre-registering hypotheses or analyses in advance of a study?		
How confident are you that the influential research findings in [Discipline] would replicate?	4. Trustworthiness of literature	Rescale from 1-5 to 0-1 Average over questions
When researchers run studies testing the canonical research findings in [Discipline], how confident are you that the studies will be able to replicate the canonical results?		
When researchers run studies testing recent research findings in [Discipline], how confident are you that the studies will be able to replicate the recent results?		
Think about the table of contents in the latest issue of [Discipline]’s top journal. How confident are you that the results of the studies will replicate?		

Questions incorporated in Measures The table shows the survey questions that are included in each measure. Each measure is then combined with other measures to produce indices (see Appendix Table 7). In the cases where multiple questions are used in a single measure, how these questions are aggregated is also described.

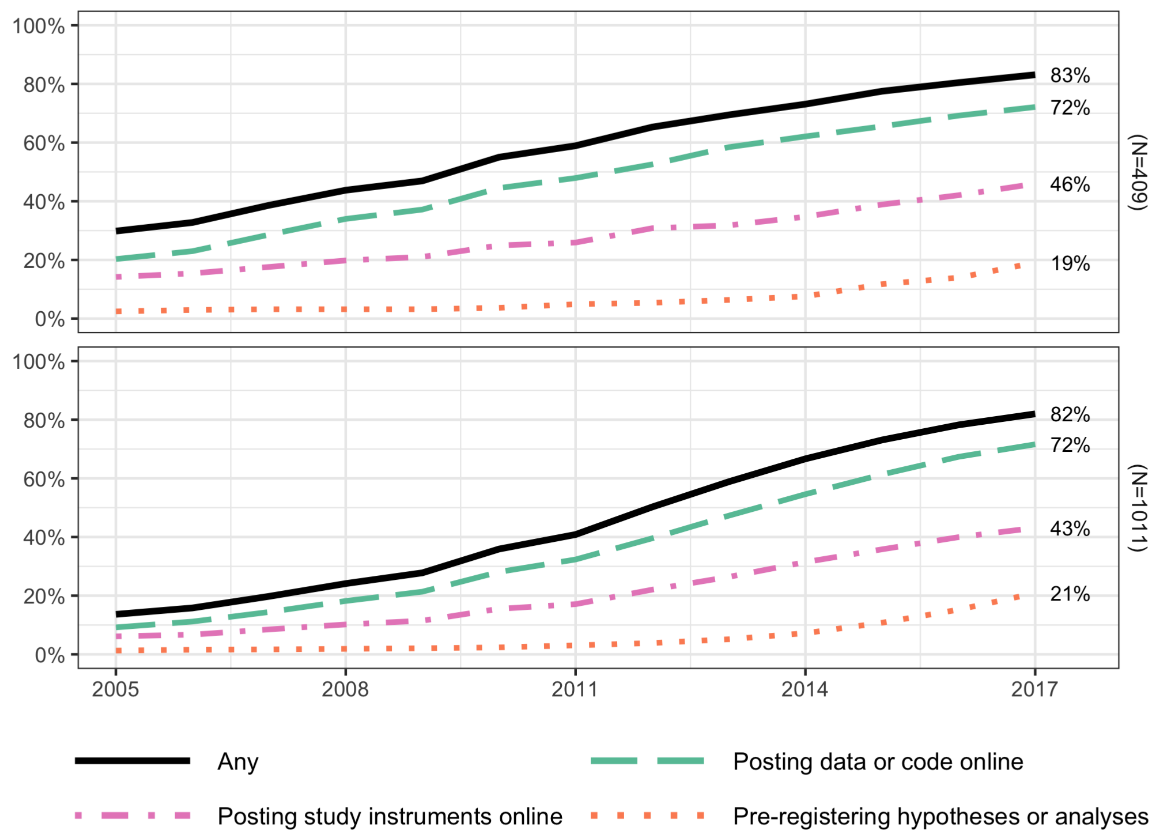
Results



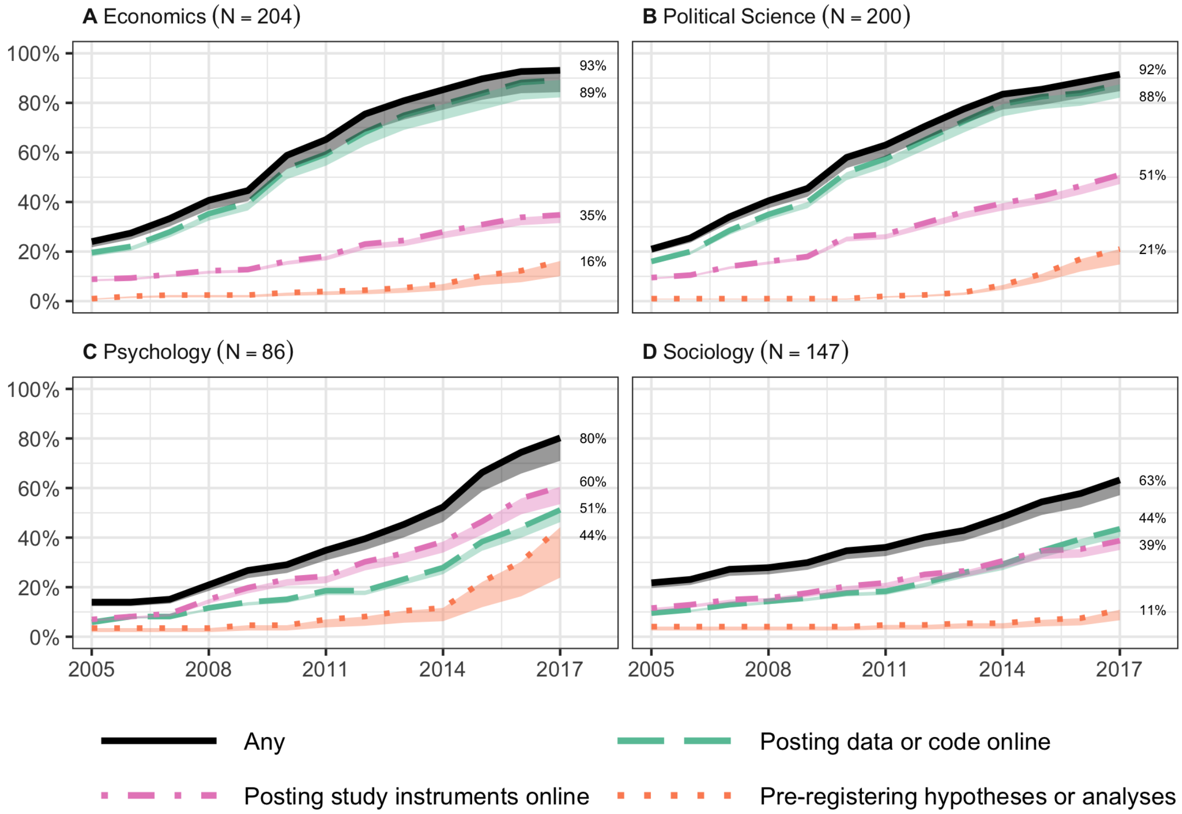
Appendix Figure 2: **Response Rates are Higher in the United States and Canada Sample.** Response rates by discipline and by career stage (PhD Student or Published Author). This figure shows the response rate by discipline and author status for all PhD Students and Published Authors whose institution was based in the United States or Canada.



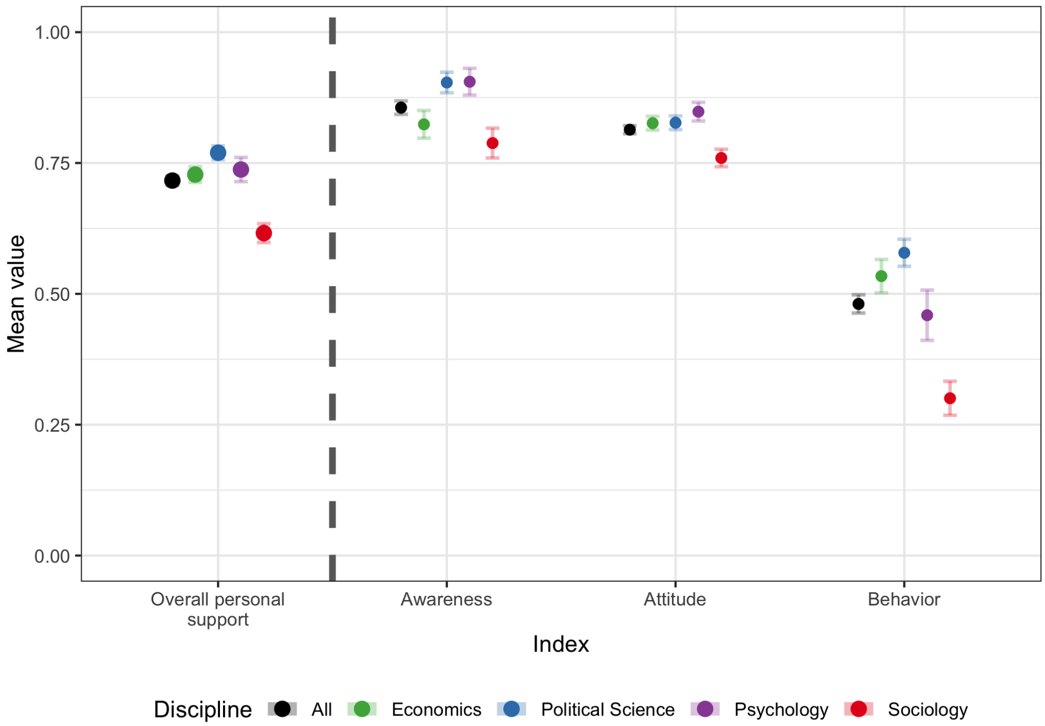
Appendix Figure 3: **Response Rate by Journal.** This figure shows the response rate by journal for the universe of journals that were used as the sampling frame for Published Authors in this project. Each panel denotes the journals for a different discipline. Numbers in grey on the right hand side of the figures show the raw number of respondents from each journal. The published author sample is drawn from the universe of authors that published in one of the above journals during the timeframe 2014-2016. However, the Published Authors are matched to any journal in the above table by any journal that they published in during the period 2010-2016. Therefore the number of Published Authors in the table above is larger than the number of Published Authors in our sample.



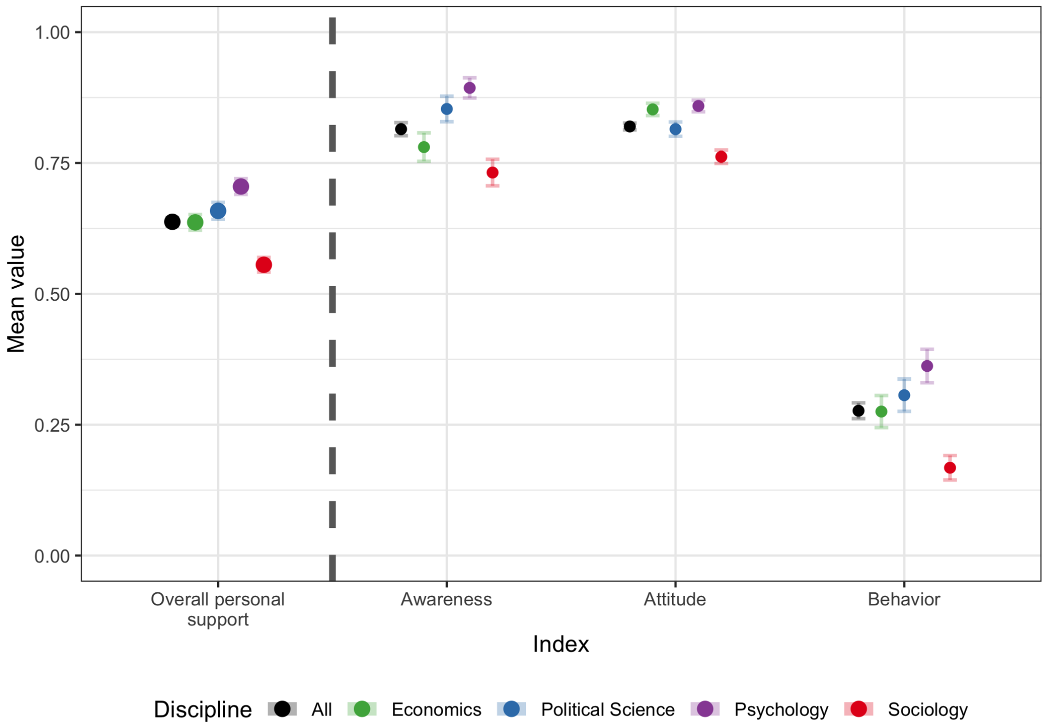
Appendix Figure 4: **Year of Adoption of Open Science Practices - Alternate Cutoff Dates.** The chart shows for a given year the proportion of Published Authors who had first completed an open science practice in that year or previously. Posting study instruments online is the response to the question "Approximately when was the first time you publicly posted study instruments online?". Posting data or code online is the response to the question "Approximately when was the first time you publicly posted data or code online?". Pre-registering hypotheses or analyses is the response to the question "Approximately when was the first time you pre-registered hypotheses or analyses in advance of a study?". The sample is restricted to Published Authors who completed their PhD by 2005 in the first panel, and Published Authors who completed their PhD prior to 2016 in the second panel.



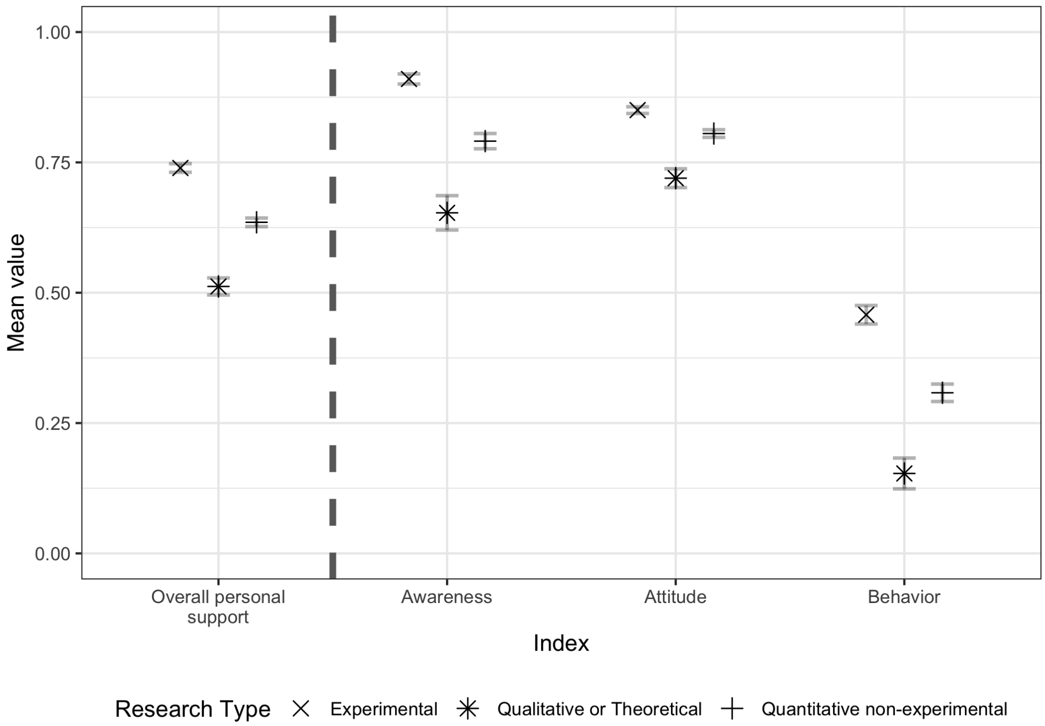
Appendix Figure 5: **Adoption by Discipline.** The chart shows for a given year the proportion of Published Authors who had first completed an open science practice in that year or previously. Posting study instruments online is the response to the question "Approximately when was the first time you publicly posted study instruments online?". Posting data or code online is the response to the question "Approximately when was the first time you publicly posted data or code online?". Pre-registering hypotheses or analyses is the response to the question "Approximately when was the first time you pre-registeredhypotheses or analyses in advance of a study?". The sample is restricted to Published Authors who completed their PhD by 2009. The bottom of the shaded region is an estimated adoption rate for the entire sample contacted, including non-respondents; the methodology for calculating the adoption rate of non-respondents is outlined in Appendix Table 10.



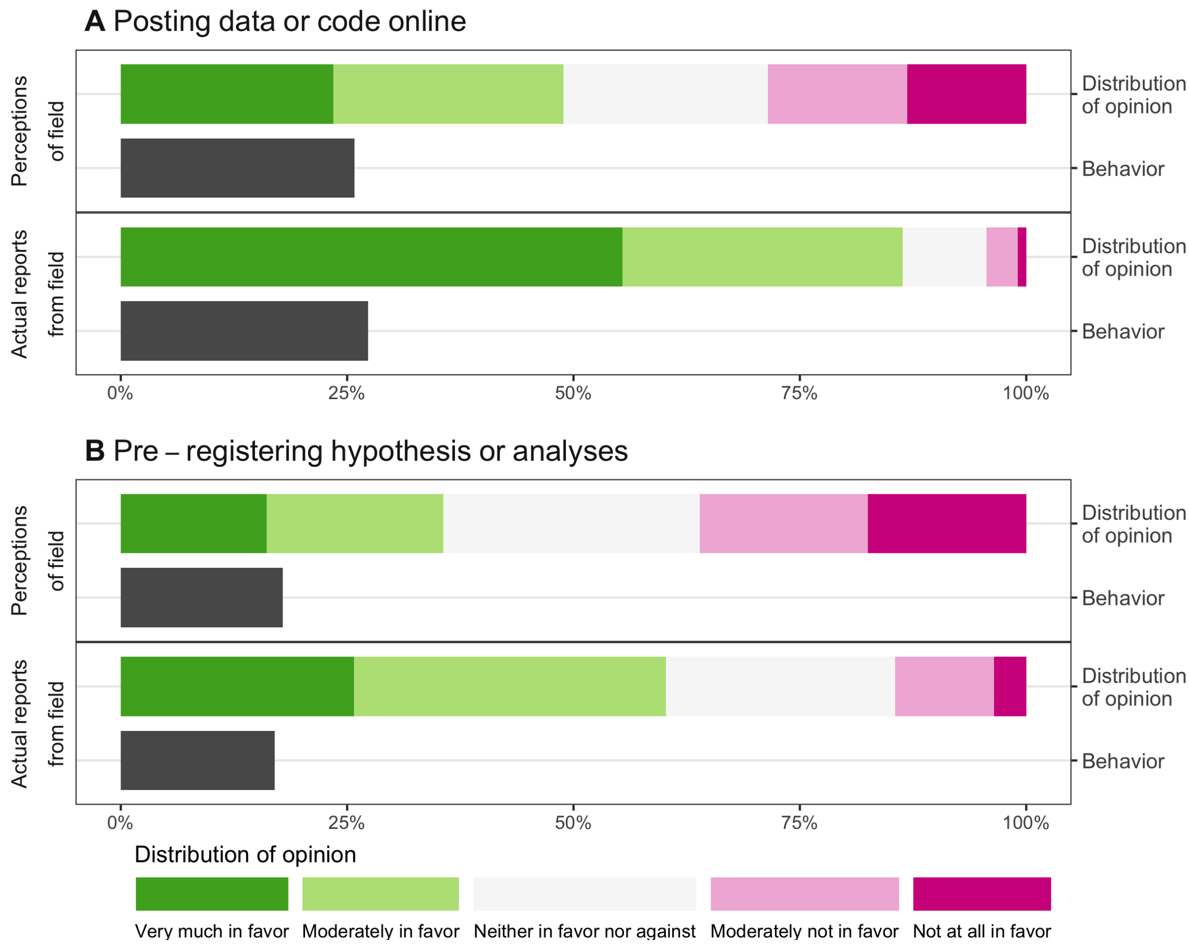
Appendix Figure 6: **Published Author Open Science Awareness, Attitudes and Behavior - By Discipline.** Lines around the dots are 95% confidence intervals for the estimates. Awareness is an index comprised of questions related to the respondent's i) Awareness of posting data and code online, ii) Awareness of posting study instruments and iii) Awareness of pre-registration. Behavior is an index comprised of questions related to the respondent's i) Behavior of posting data and code online, ii) Behavior of posting study instruments and iii) Behavior of pre-registration. Attitudes is an index comprised of questions related to the respondent's i) Attitudes of posting data and code online, ii) Attitudes of posting study instruments and iii) Attitudes of pre-registration. Overall Personal Support is an average of the three indices. The questions and methodology that are used to construct the indices can be found in Appendix Table 7.



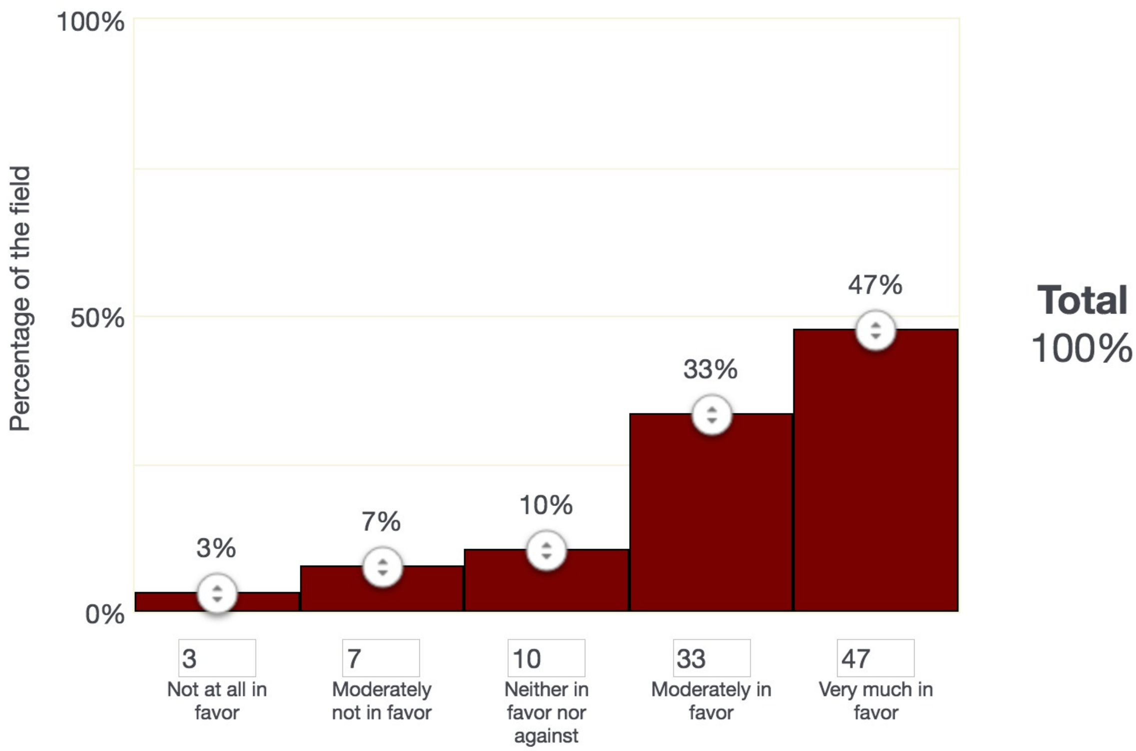
Appendix Figure 7: **Student Open Science Awareness, Attitudes and Behavior - By Discipline.** Grey lines around the dots are 95% confidence intervals for the estimates. Awareness is an index comprised of questions related to the respondent's i) Awareness of posting data and code online, ii) Awareness of posting study instruments and iii) Awareness of pre-registration. Behavior is an index comprised of questions related to the respondent's i) Behavior of posting data and code online, ii) Behavior of posting study instruments and iii) Behavior of pre-registration. Attitudes is an index comprised of questions related to the respondent's i) Attitudes of posting data and code online, ii) Attitudes of posting study instruments and iii) Attitudes of pre-registration. Overall Personal Support is an average of the three indices. The questions and methodology that are used to construct the indices can be found in Appendix Table 7.



Appendix Figure 8: **Open Science Awareness, Attitudes and Behavior - By Research Type.** Grey lines around the dots are 95% confidence intervals for the estimates. Awareness is an index comprised of questions related to the respondent's i) Awareness of posting data and code online, ii) Awareness of posting study instruments and iii) Awareness of pre-registration. Behavior is an index comprised of questions related to the respondent's i) Behavior of posting data and code online, ii) Behavior of posting study instruments and iii) Behavior of pre-registration. Attitudes is an index comprised of questions related to the respondent's i) Attitudes of posting data and code online, ii) Attitudes of posting study instruments and iii) Attitudes of pre-registration. Overall Personal Support is an average of the three indices. The questions and methodology that are used to construct the indices can be found in Appendix Table 7.



Appendix Figure 9: **Perceived and Actual Support for Open Science - Students.** The chart shows differences between perceived and actual support for two practices: posting data or code online and pre-registering hypotheses or analyses. The sample is restricted to PhD Students. Within each panel, the first bar shows the perceived distribution of support for the practice among Students. This is constructed by asking individuals what percentage of researchers in their field they believe fall into each opinion category, and then averaging over their responses. The solid black bar below shows the fraction of researchers in their field they believe have done the practice. The third bar in the panel shows the distribution of support for the practice constructed using the responses elicited from students. The final solid black bar shows the proportion of students who have actually done the stated practices, using the responses elicited from our survey. Colors indicate the level of support, with green indicating more and red indicating less support.



Appendix Figure 10: **Dynamic Histogram used by survey respondents to indicate perceived support for open science practices.** This chart shows the dynamic histogram that survey respondents used to indicate perceived support for open science in their field. Bars need to add up to 100% for respondents to proceed in the survey.

Appendix Table 9: Differences in Observables for Published Authors completing and not completing survey in Economics Subfield Validation Data

	Overall (1)	Respondent (2)	Nonrespondent (3)	Difference (2) - (3)
Share of sample:				
— Theory Focused	0.19	0.15	0.22	-0.07 (-1.58)
— Macro/Finance Focused	0.26	0.16	0.33	-0.17 (-3.28)***
— not Theory/Macro/Finance Focused	0.55	0.69	0.45	0.24 (4.29)***
Verified Open Science Behavior				
— all Economics Published Author	0.59	0.65	0.55	0.10 (1.81)*
— among Theory Focused	0.35	0.39	0.32	0.07 (0.54)
— among Macro/Finance Focused	0.56	0.58	0.55	0.04 (0.33)
— not Theory/Macro/Finance Focused	0.69	0.73	0.67	0.06 (0.76)
N	753	300	100	

This table shows the percentage of economics Published Authors who work in different subfields among those who responded and did not respond to the survey. The first panel reports response rates and share of each sample for each subfield. Column 1 shows the response rate for each subfield. Columns 2 and 3 show the share of respondents and non-respondents identifying with each subfield respectively. Panel B shows the fraction of individuals in each subfield for whom we verified open science behavior during our audit activity. For respondents, the subfield is determined by the subfield that the respondent listed in our survey. For non-respondents, we constructed the individual's subfield in an audit activity that was completed between March 15 2019 and April 15 2019. In this activity, we used publicly available data sources to collect data on the primary subfield of these non-respondents. We manually collected all of the subfields that an individual listed working in on their website or CV. After these subfields were collected we manually categorised these subfields into one of three categories. The first of these was "Theory focused", which is categorised as any individual who listed Microeconomic Theory or Econometrics as a primary subfield. The second was "Macroeconomics/Finance", which was any author who listed Macroeconomics or Finance as a primary field. Finally, all other authors were categorised in the residual category. The final column in the table provides t-statistics for tests for differences in the mean between those respondents and non-respondents. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 10: Differences in Stated and Observed Open Science Behavior for Economics Published Authors and Estimates of Open Science Behavior for Economics Published Authors Non-Respondents based on Economics Subfield Validation Data

Parameter	Any (1)	Posting data or code online (2)	Posting study instruments (3)	Pre-registering hypotheses or analyses (4)
Respondent				
Share of Respondents Doing Practice (self-report) (S_R)	84.0%	73.0%	44.3%	20.3%
Share of Respondents Doing Practice (validation) (V_R)	65.3%	63.3%	34.4%	19.0%
Difference between S_R and V_R (D_R)	18.7%	9.7%	9.8%	1.3%
Non-respondent				
Predicted share of non-respondents doing practice ($\widehat{S_N}$)	70.7%	63.4%	37.3%	7.5%
Share of non-respondents verified doing practice (V_N)	55.0%	55.0%	29.0%	7.0%
Difference between $\widehat{S_N}$ and V_N ($\widehat{D_N}$)	15.7%	8.4%	8.3%	0.5%
$\frac{V_N}{V_R}$	84.2%	86.8%	84.2%	36.8%
Share of Practices Verified ($\frac{V_R}{S_R}$)	77.7%	86.7%	77.7%	93.6%

This table presents stated and observed open science behavior for Published Authors in Economics who are respondents and non-respondents in our sample. Observed behavior comes from our audit of all the economists who completed the survey and a random sample of 100 economists who did not complete survey. This audit was completed between March 15, 2019 and April 15, 2019. For pre-registration and posting data and code online, S_R is the percentage of respondents who report engaging in the specified open science practice in our survey. V_R is the percentage of Published Author respondents who we find in our audit to engage in the open science practice. D_R reports the difference between the two. V_N is the percentage of non-respondents in our audited sample that we verify have done an open science practice. $\widehat{S_N}$ is an imputed value for the stated percentage of non-respondents that would have reported doing an open-science practice had they been surveyed. To estimate this, we multiply the audit value V_N by the ratio between stated and observed of respondents (i.e the ratio $\frac{S_R}{V_R}$). $\widehat{D_N}$ is the difference between $\widehat{S_N}$ and V_N. Since we did not conduct an audit for "Posting study instruments online", the "Any" category refers either "Posting data or code online" or "Pre-registering hypotheses or analyses". And "Posting study instruments online" therefore V_R is imputed using the ratio of S_R to V_R in the "Any" category. The remainder of the methodology for this open science practice is the same as listed above.

Appendix Table 11: Characteristics of those Completing Survey

	Completed Survey				
	All	Psychology	Economics	Political Science	Sociology
	(1)	(2)	(3)	(4)	(5)
USA and Canada	0.13***	0.14***	0.11***	0.10**	0.11***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)
Publication Count (right winsorized)	0.02***	0.01	0.01	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.26***	0.17***	0.31***	0.43***	0.27***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)
Observations	2,983	708	753	763	759

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is an indicator variable for whether the individual contacted completed the survey. The covariates are observable characteristics of the individual contacted. The sample is limited to Published Authors. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 12: Differences in Sub Indices across Disciplines

	Posting data or code online		Posting study instruments		Pre-registering hypotheses or analyses	
	(1)	(2)	(3)	(4)	(5)	(6)
Economics	0.17***	0.16***	−0.01	−0.02*	0.07***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Political Science	0.16***	0.15***	0.06***	0.05***	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Psychology	0.06***	0.07***	0.08***	0.09***	0.16***	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years since started PhD		0.0001		0.002***		−0.002***
		(0.0003)		(0.001)		(0.0004)
Male		0.04***		0.03***		0.01**
		(0.01)		(0.01)		(0.01)
Tenured		0.03***		0.02		−0.01
		(0.01)		(0.01)		(0.01)
Leadership Position		−0.005		0.003		0.001
		(0.01)		(0.01)		(0.01)
USA and Canada		−0.01		−0.02		−0.01
		(0.01)		(0.01)		(0.01)
Constant	0.45***	0.44***	0.65***	0.63***	0.33***	0.36***
	(0.005)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	2,707	2,663	2,707	2,663	2,707	2,663

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the sub indices described in appendix table 7. The covariates are indicator variables for the discipline of the respondent. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted discipline in the regressions are Sociology Published Authors and PhD Students. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 13: Differences in Observables for those Completing and Not Completing Survey

Variable	Overall (1)	Respondent (2)	Nonrespondent (3)	Difference (2) - (3)
All				
Publication Count (right winsorized)	2.08	2.21	1.99	0.22 (4.24)***
USA and Canada	0.68	0.76	0.63	0.13 (7.64)***
N	2983	1181	1802	
Economics				
Publication Count (right winsorized)	2.29	2.37	2.23	0.14 (1.28)
USA and Canada	0.65	0.72	0.61	0.11 (3.07)***
N	753	300	453	
Political Science				
Publication Count (right winsorized)	2.38	2.45	2.31	0.14 (1.27)
USA and Canada	0.76	0.80	0.72	0.08 (2.56)**
N	763	407	356	
Psychology				
Publication Count (right winsorized)	1.74	1.81	1.71	0.1 (0.96)
USA and Canada	0.59	0.72	0.54	0.18 (4.48)***
N	708	185	523	
Sociology				
Publication Count (right winsorized)	1.89	1.98	1.84	0.14 (1.47)
USA and Canada	0.71	0.77	0.68	0.09 (2.83)***
N	759	289	470	

This table presents differences in means for the number of publications and geographic location of the university for published scholars who did and did not complete the survey. The third column shows differences in means and t-statistics in parentheses. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 14: Relationship between Past and Current Open Science Behavior

	Used in Last Paper:			
	Any practice	Posting data or code online	Posting study instruments	Pre-registering hypotheses or analyses
	(1)	(2)	(3)	(4)
Has done any practice ever	0.73***			
	(0.03)			
Has done posting data or code online		0.69***		
		(0.02)		
Has done posting study instruments			0.59***	
			(0.02)	
Has done pre-registering hypotheses or analyses				0.55***
				(0.02)
Constant	0.01	0.01	0.003	0.002
	(0.03)	(0.02)	(0.01)	(0.01)
Observations	1,182	1,182	1,182	1,182

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is an indicator variable for whether the individual conducted an open science behavior in their last paper. The covariates are indicator variables for whether the individual had ever undertaken such an open scienncee practice. The sample is limited to Published Authors. * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 15: Differences in Broad Indices across Disciplines

	Personal support (no norms)		Norms		Overall (includes norms)		Trustworthiness of literature	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Economics	0.10***	0.08***	0.12***	0.12***	0.08***	0.07***	0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Political Science	0.13***	0.12***	0.11***	0.10***	0.10***	0.09***	−0.04***	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Psychology	0.14***	0.15***	0.09***	0.09***	0.10***	0.10***	−0.05***	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years since started PhD		0.001*		−0.001***		0.0001		−0.0004
		(0.0004)		(0.0003)		(0.0003)		(0.0005)
Male		0.05***		0.01**		0.03***		−0.02***
		(0.01)		(0.005)		(0.005)		(0.01)
Tenured		0.03**		0.01		0.02**		0.06***
		(0.01)		(0.01)		(0.01)		(0.01)
Leadership Position		−0.002		−0.002		−0.0002		0.01
		(0.01)		(0.005)		(0.005)		(0.01)
USA and Canada		−0.03***		−0.01		−0.02**		−0.03***
		(0.01)		(0.01)		(0.01)		(0.01)
Constant	0.58***	0.57***	0.31***	0.32***	0.48***	0.47***	0.64***	0.66***
	(0.01)	(0.01)	(0.004)	(0.01)	(0.004)	(0.01)	(0.01)	(0.01)
Observations	2,707	2,663	2,703	2,660	2,707	2,663	2,703	2,660

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the broad indices described in appendix table 7. The covariates are indicator variables for the discipline of the respondent. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted discipline in the regressions are Sociology Published Authors and PhD Students. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 16: Differences in Broad Indices by Author Type

	Personal support (no norms)		Norms		Overall (includes norms)		Trustworthiness of literature	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Published Author	0.08***	0.09***	0.002	0.02**	0.04***	0.05***	0.04***	0.02*
	(0.01)	(0.01)	(0.005)	(0.01)	(0.005)	(0.01)	(0.01)	(0.01)
Years since started PhD		−0.002***		−0.002***		−0.002***		−0.001
		(0.0005)		(0.0004)		(0.0004)		(0.001)
Male		0.05***		0.03***		0.03***		−0.02**
		(0.01)		(0.01)		(0.005)		(0.01)
Tenured		0.002		0.02		0.005		0.05***
		(0.01)		(0.01)		(0.01)		(0.01)
Leadership Position		0.002		−0.01		0.002		0.01
		(0.01)		(0.01)		(0.005)		(0.01)
USA and Canada		−0.005		−0.003		0.0004		−0.03
		(0.01)		(0.01)		(0.01)		(0.01)
Constant	0.64***	0.63***	0.39***	0.38***	0.53***	0.52***	0.60***	0.63***
	(0.004)	(0.01)	(0.003)	(0.01)	(0.003)	(0.01)	(0.004)	(0.01)
Observations	2,707	2,663	2,703	2,660	2,707	2,663	2,703	2,660

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the broad indices described in appendix table 7. The covariates are indicator variables for the whether the respondent has published in one of the journals in appendix tables 2 through 5. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted discipline in the regressions are PhD Students. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 17: Differences in Broad Indices across Disciplines and Author type

	Personal support (no norms)		Norms		Overall (includes norms)		Trustworthiness of literature	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Published Author	0.06***	0.07***	−0.01	0.01	0.03***	0.04***	0.03**	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Economics	0.08***	0.07***	0.12***	0.11***	0.08***	0.07***	−0.003	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Political Science	0.10***	0.10***	0.10***	0.10***	0.08***	0.08***	−0.05***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Psychology	0.15***	0.15***	0.09***	0.09***	0.11***	0.11***	−0.05***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Published Author:Economics	0.03	0.03	0.01	0.01	0.01	0.01	0.03	0.02
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Published Author:Political Science	0.05	0.04**	0.01	0.01	0.03	0.02*	0.01	0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Published Author:Psychology	−0.03	−0.04	−0.01	−0.01	−0.02	−0.02	−0.001	0.004
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Years since started PhD		−0.001**		−0.001***		−0.001***		−0.001**
		(0.0005)		(0.0004)		(0.0003)		(0.001)
Male		0.05***		0.01**		0.02***		−0.02***
		(0.01)		(0.005)		(0.005)		(0.01)
Tenured		−0.004		0.004		−0.0001		0.05***
		(0.01)		(0.01)		(0.01)		(0.01)
Leadership Position		−0.0003		−0.002		0.002		0.01
		(0.01)		(0.01)		(0.005)		(0.01)
USA and Canada		−0.01		−0.002		−0.0002		−0.02
		(0.01)		(0.01)		(0.01)		(0.01)
Constant	0.56***	0.55***	0.31***	0.32***	0.46***	0.46***	0.62***	0.66***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,707	2,663	2,703	2,660	2,707	2,663	2,703	2,660

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the broad indices described in appendix table 7. The covariates are indicator variables for the discipline and author type of the respondent. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted category in the regressions are Sociology PhD Students. Coefficients on disciplines not interacted with Published Authors are effects for PhD Students in these disciplines. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 18: Differences in Sub Indices across Disciplines

	Awareness		Attitude		Behavior		Descriptive Norms		Prescriptive Norms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Economics	0.05^{***}	0.03^{**}	0.08^{***}	0.07^{***}	0.17^{***}	0.13^{***}	0.13^{***}	0.13^{***}	0.11^{***}	0.11^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Political Science	0.12^{***}	0.12^{***}	0.06^{***}	0.06^{***}	0.22^{***}	0.20^{***}	0.14^{***}	0.14^{***}	0.08^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Psychology	0.14^{***}	0.15^{***}	0.09^{***}	0.09^{***}	0.17^{***}	0.20^{***}	0.09^{***}	0.09^{***}	0.08^{***}	0.08^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Years since started PhD		−0.001		-0.001^{**}		0.004^{***}		-0.001^{***}		−0.001
		(0.001)		(0.0004)		(0.001)		(0.0004)		(0.0004)
Male		0.05^{***}		0.02^{***}		0.09^{***}		0.001		0.02^{***}
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
Tenured		0.04^{**}		-0.02^{**}		0.06^{**}		0.02^{**}		−0.01
		(0.02)		(0.01)		(0.02)		(0.01)		(0.01)
Leadership Position		−0.01		−0.01		0.01		0.0001		−0.004
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
USA and Canada		0.004		-0.03^{***}		-0.07^{***}		0.01		−0.02
		(0.02)		(0.01)		(0.02)		(0.01)		(0.01)
Constant	0.75^{***}	0.73^{***}	0.76^{***}	0.80^{***}	0.22^{***}	0.19^{***}	0.14^{***}	0.14^{***}	0.48^{***}	0.50^{***}
	(0.01)	(0.02)	(0.005)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,707	2,663	2,706	2,662	2,667	2,623	2,700	2,657	2,674	2,634

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the sub indices described in appendix table 7. The covariates are indicator variables for the discipline of the respondent. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted discipline in the regressions are Sociology Published Authors and PhD Students. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 19: Differences in Sub Indices by Author Type

	Awareness		Attitude		Behavior		Descriptive Norms		Prescriptive Norms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Published Author	0.04***	0.07***	−0.01	0.02**	0.20***	0.19***	0.001	0.01	0.004	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Years since started PhD		−0.003***		−0.002***		−0.001		−0.002***		−0.001***
		(0.001)		(0.0004)		(0.001)		(0.0005)		(0.0005)
Male		0.04***		0.02***		0.09***		0.02***		0.03***
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
Tenured		0.02		−0.02**		0.01		0.03***		−0.01
		(0.02)		(0.01)		(0.02)		(0.01)		(0.01)
Leadership Position		−0.0001		−0.01		0.01		−0.004		−0.01
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
USA and Canada		0.02		−0.03***		−0.01		0.01		−0.01
		(0.02)		(0.01)		(0.02)		(0.01)		(0.01)
Constant	0.81***	0.78***	0.82***	0.85***	0.28***	0.24***	0.23***	0.22***	0.54***	0.55***
	(0.01)	(0.02)	(0.003)	(0.01)	(0.01)	(0.02)	(0.004)	(0.01)	(0.004)	(0.01)
Observations	2,707	2,663	2,706	2,662	2,667	2,623	2,700	2,657	2,674	2,634

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the sub indices described in appendix table 7. The covariates are indicator variables for the whether the respondent has published in one of the journals in appendix tables 2 through 5. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted discipline in the regressions are PhD Students. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 20: Differences in Sub Indices across Disciplines and Author type

	Awareness		Attitude		Behavior		Descriptive Norms		Prescriptive Norms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Published Author	0.06***	0.08***	−0.002	0.02*	0.13***	0.13***	−0.01	0.003	−0.005	0.02
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Economics	0.05***	0.04**	0.09***	0.08***	0.11***	0.09***	0.14***	0.14***	0.10***	0.10***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Political Science	0.12***	0.12***	0.05***	0.05***	0.14***	0.13***	0.13***	0.13***	0.08***	0.07***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Psychology	0.16***	0.17***	0.10***	0.10***	0.19***	0.20***	0.10***	0.10***	0.08***	0.08***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Published Author:Economics	−0.01	−0.01	−0.02	−0.02	0.13	0.11***	−0.01	−0.01	0.02	0.02
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Published Author:Political Science	−0.01	−0.02	0.01	0.01	0.14	0.13***	0.02	0.02	0.001	−0.002
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)
Published Author:Psychology	−0.04	−0.05	−0.01	−0.02	−0.04	−0.05	−0.03	−0.03	0.004	−0.003
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Years since started PhD		−0.002**		−0.001***		0.0001		−0.001**		−0.001**
		(0.001)		(0.0004)		(0.001)		(0.0005)		(0.0005)
Male		0.05***		0.02***		0.08***		0.0004		0.02***
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
Tenured		0.02		−0.03**		−0.01		0.02		−0.02
		(0.02)		(0.01)		(0.02)		(0.01)		(0.01)
Leadership Position		−0.004		−0.01		0.01		0.001		−0.01
		(0.01)		(0.01)		(0.01)		(0.01)		(0.01)
USA and Canada		0.02		−0.03***		−0.01		0.004		−0.01
		(0.02)		(0.01)		(0.02)		(0.01)		(0.01)
Constant	0.73***	0.70***	0.76***	0.79***	0.17***	0.14***	0.14***	0.14***	0.48***	0.49***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	2,707	2,663	2,706	2,662	2,667	2,623	2,700	2,657	2,674	2,634

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the sub indices described in appendix table 7. The covariates are indicator variables for the discipline and author type of the respondent. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted category in the regressions are Sociology PhD Students. Coefficients on disciplines not interacted with Published Authors are effects for PhD Students in these disciplines. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 21: Differences in Sub Indices by Author Type

	Posting data or code online		Posting study instruments		Pre-registering hypotheses or analyses	
	(1)	(2)	(3)	(4)	(5)	(6)
Published Author	0.06***	0.06***	0.08***	0.08***	−0.02***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years since started PhD		−0.002***		−0.0004		−0.003***
		(0.0004)		(0.001)		(0.0005)
Male		0.07***		0.01		0.01
		(0.01)		(0.01)		(0.01)
Tenured		0.04***		−0.01		−0.02
		(0.01)		(0.01)		(0.01)
Leadership Position		−0.01		0.01		0.004
		(0.01)		(0.01)		(0.01)
USA and Canada		0.01		0.004		−0.01
		(0.01)		(0.01)		(0.01)
Constant	0.52***	0.49***	0.65***	0.64***	0.42***	0.43***
	(0.004)	(0.01)	(0.01)	(0.02)	(0.004)	(0.01)
Observations	2,707	2,663	2,707	2,663	2,707	2,663

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the sub indices described in appendix table 7. The covariates are indicator variables for the whether the respondent has published in one of the journals in appendix tables 2 through 5. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted discipline in the regressions are PhD Students. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Appendix Table 22: Differences in Sub Indices across Disciplines and Author type

	Posting data or code online		Posting study instruments		Pre-registering hypotheses or analyses	
	(1)	(2)	(3)	(4)	(5)	(6)
Published Author	0.02**	0.03**	0.08***	0.08***	−0.01	0.02*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Economics	0.15***	0.14***	−0.01	−0.01	0.08***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Political Science	0.13***	0.12***	0.04***	0.04***	0.09***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Psychology	0.08***	0.08***	0.09***	0.09***	0.15***	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Published Author:Economics	0.04	0.04***	−0.01	−0.02	−0.01	−0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Published Author:Political Science	0.07	0.06***	0.02	0.02	−0.01	−0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Published Author:Psychology	−0.03	−0.03*	−0.03	−0.03	0.01	−0.0001
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Years since started PhD		−0.001**		0.0001		−0.002***
		(0.0004)		(0.001)		(0.0004)
Male		0.04***		0.02***		0.01**
		(0.005)		(0.01)		(0.01)
Tenured		0.01		−0.002		−0.01
		(0.01)		(0.01)		(0.01)
Leadership Position		−0.005		0.01		0.002
		(0.01)		(0.01)		(0.01)
USA and Canada		0.002		0.001		−0.004
		(0.01)		(0.01)		(0.01)
Constant	0.44***	0.43***	0.62***	0.60***	0.34***	0.35***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	2,707	2,663	2,707	2,663	2,707	2,663

Note:

This table presents regression coefficients and standard errors from ordinary least squares regressions. The outcome variable in each regression is one of the sub indices described in appendix table 7. The covariates are indicator variables for the discipline and author type of the respondent. In odd numbered specifications no other control variables are included. In even numbered specifications individual-level covariates are included. The omitted category in the regressions are Sociology PhD Students. Coefficients on disciplines not interacted with Published Authors are effects for PhD Students in these disciplines. Significance stars are indicated for standard errors computed using a multiple testing adjustment to address risk of false positives. In particular, we use the False Discovery Rate (FDR) adjustment in Benjamini, Krieger, and Yekutieli (2006) and discussed in Anderson (2008). * indicates significance at the 10% level, ** indicates significance at the 5% level and *** indicates significance at the 1% level.

Supplementary materials B

This project's OSF page

The survey conducted, uploaded to OSF

The link to the Pre-Analysis Plan, uploaded to OSF