



Questionable Research Practices and Open Science in Quantitative Criminology

Jason M. Chin^{1,2} · Justin T. Pickett³ · Simine Vazire⁴ · Alex O. Holcombe⁵

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Abstract

Objectives Questionable research practices (QRPs) lead to incorrect research results and contribute to irreproducibility in science. Researchers and institutions have proposed open science practices (OSPs) to improve the detectability of QRPs and the credibility of science. We examine the prevalence of QRPs and OSPs in criminology, and researchers' opinions of those practices.

Methods We administered an anonymous survey to authors of articles published in criminology journals. Respondents self-reported their own use of 10 QRPs and 5 OSPs. They also estimated the prevalence of use by others, and reported their attitudes toward the practices.

Results QRPs and OSPs are both common in quantitative criminology, about as common as they are in other fields. Criminologists who responded to our survey support using QRPs in some circumstances, but are even more supportive of using OSPs. We did not detect a significant relationship between methodological training and either QRP or OSP use. Support for QRPs is negatively and significantly associated with support for OSPs. Perceived prevalence estimates for some practices resembled a uniform distribution, suggesting criminologists have little knowledge of the proportion of researchers that engage in certain questionable practices.

Conclusions Most quantitative criminologists in our sample have used QRPs, and many have used multiple QRPs. Moreover, there was substantial support for QRPs, raising questions about the validity and reproducibility of published criminological research. We found promising levels of OSP use, albeit at levels lagging what researchers endorse. The findings thus suggest that additional reforms are needed to decrease QRP use and increase the use of OSPs.

Keywords Questionable research practices · Meta-research · Open science · Reproducibility

✉ Jason M. Chin
jason.chin@sydney.edu.au

Extended author information available on the last page of the article

Introduction

It is not hard for scientists, including criminologists, to get whatever research findings they want—evidence that a criminal justice policy or program is effective, support for a favored theory or new hypothesis, statistical significance for a surprising interaction effect (Ritchie 2020; Sweeten 2020). Sufficient use of questionable research practices (QRPs) (Simmons et al. 2011) will do the trick. QRPs inflate a field's false positive rate (Simmons et al. 2011) by making it easy for scientists to turn “ugly initial results ... into beautiful articles” (O’Boyle et al. 2017, p. 376). They are common in every field where they have been assessed, including psychology (John et al. 2012), political science (Franco et al. 2015), management (O’Boyle et al. 2017), education (Makel et al. 2021), quantitative communication (Bakker et al. 2020), and ecology and evolutionary biology (Fraser et al. 2018).

Are QRPs common in criminology? Some signs suggest the answer is yes (Burt 2020). Criminologists are more likely to find desired effects when using weaker research designs that give them more opportunities for undisclosed flexibility (Weisburd and Lum 2001; Welsh et al. 2011). Indeed, this is a consistent finding in criminological meta-analyses: quasi-experiments produce much larger effects and results that are more often statistically significant than RCTs (e.g., Braga et al. 2014, 2018). The same is true in psychology (Kvarven et al. 2020), where QRP use has been well-documented (John et al. 2012; Agnoli et al. 2017; Rabelo et al. 2020). Additionally, there is a sizable inverse relationship between sample size and effect size in criminology (Nelson et al. 2015), which is another telltale sign that something is amiss (Gelman et al. 2020; Levine et al. 2009). As importantly, published experiments in criminology often differ from the plan described at the proposal stage, and the more they differ the larger the published effect size, suggesting criminologists deviate selectively from research protocols in a way that exaggerates results (Wooditch et al. 2020). Despite this suggestive evidence, however, there have been no surveys on QRP use in criminology, as there have been in other disciplines.

Open Science Practices (OSPs) may help combat the negative effects of QRPs (Ritchie 2020; Simmons et al. 2011). For example, preregistering analysis plans and publicly posting data and replication code, make it possible for outside researchers not only to replicate findings, but also to evaluate the effects of specific analytical decisions, such as deviations from preregistered protocols. OSPs may also deter QRPs if they increase the perceived certainty of QRP detection (Apel 2013). A movement is underway in many fields to increase the use of OSPs, and even to institutionalize them at journals and funding organizations (Ritchie 2020; Vazire 2018). However, even less survey evidence exists about the prevalence of OSPs than QRPs across disciplines (Bakker et al. 2020; Makel et al. 2021). As with QRPs, there have been no surveys on OSP use in criminology.

To address this void, in 2020 we administered an anonymous survey on QRPs and OSPs to a sample of criminologists. We designed the survey to mirror those fielded in other disciplines (e.g., John et al. 2012; Fraser et al. 2018). The survey measured behavior and relevant attitudes. In what follows, we first outline the various QRPs that criminologists may use and review the evidence from other disciplines about their prevalence and effects. We then discuss the open science movement and the recommended pro-transparency research practices that have emerged from it. Next, we describe our study and its results, which provide the first large scale estimates of the prevalence of QRPs and OSPs in criminology.

Questionable Research Practices (QRPs)

QRPs include the practice known as *p*-hacking (Bishop 2019), other inappropriate uses of researcher degrees of freedom (Simmons et al. 2011) or the exploitation of analytic flexibility (Beerdson 2021), and publication bias (Fanelli 2012). All of these terms refer to a set of practices that, when not reported transparently, distort the accuracy of research reports, typically in a way that exaggerates effect sizes or produces statistically significant results. QRPs often involve hidden research decisions that are based on whether they yield statistically significant results, including decisions regarding when to stop collecting data, which analytic method to use and report, which variables to include in a model, how to code those variables, whether to exclude outliers, and whether to write up a study (John et al. 2012; see Table 1). Such practices produce biases because undisclosed flexibility (e.g., trying out several different covariates, outlier exclusion thresholds, or subgroup analyses) allows researchers to selectively under- or over-fit models and exploit noise in a way that goes uncorrected (e.g., through *p*-value corrections like Bonferroni) and unreported (Gelman and Loken 2014; Simmons et al. 2011), inflating the false positive rate.

Some authors engage in QRPs without being aware of their pernicious effects. Editors and reviewers may even encourage QRPs, such as testing for non-hypothesized interaction effects and presenting them as planned, or only including them in the manuscript if they are significant, or conducting and selectively reporting post-hoc subgroup analyses. Other times, editors and reviewers may incentivize the use of QRPs by devaluing non-significant findings—for example, by selectively applying critiques to non-significant results that might just as easily be applied to significant results. For these reasons, greater awareness of QRP use and their consequences in criminology is beneficial.

A growing body of evidence points to QRPs as a primary reason that many studies are proving difficult to replicate. Some researchers have admitted using QRPs, after their findings failed to replicate (Carney 2016; Rohrer et al. 2018). For instance, the lead author of psychology's controversial power pose studies later stated: "The self-report DV was *p*-hacked in that many different power pose questions were asked and those chosen were the ones that 'worked'" (Carney 2016). Similarly, a group of authors studying bilingualism and cognitive advantage admitted that they selectively reported findings that confirmed their hypothesis: "We ourselves are guilty ... the only experiment that we submitted for publication was the one showing an effect of bilingualism" (de Bruin et al. 2015, pp. 99–100).

Systematic research supports the association between QRPs and irreplicable research. For instance, Simmons and colleagues (2011) used simulations to estimate the effect of using four QRPs (selective reporting of two DVs, deciding whether or not to add 10 extra observations based on the statistical significance of the result, selectively adding or removing covariates, selectively including or dropping a condition) on the rate of false positive findings. They applied the QRPs to randomly generated data under the null hypothesis (i.e., when all statistically significant results are false positives), and found that using just those four QRPs inflated the false positive rate from the nominal 5% (α) to over 60%. One study in the field of management found evidence that the use of QRPs after dissertation defenses, but before resultant articles were published, led to a 21-percentage-point increase in statistically significant results, which corresponded "to more than a doubling of the ratio of supported to unsupported hypotheses" (O'Boyle et al. 2017, p. 388; see also Cairo et al. 2020 in psychology).

How common is QRP use? There are several methods that can be used to investigate this question (Bakker et al. 2020). One is to compare the shape of the distribution of

Table 1 Prior research: prevalence of QRPs and OSPs in other disciplines

Practice ¹	Psychology ³						
	John et al. (2012) ²	Agnoli et al. (2017)	Rabelo et al. (2020)	Fraser et al. (2018)	Fraser et al. (2018)	Makel et al. (2021)	Bakker et al. (2020)
Omit non-significant studies or variables	46 (485)	40 (217)	55 (232)	–	–	62 (783)	60
Underreport outcomes	63 (486)	48 (219)	22 (232)	64	64	–	–
Underreport conditions	28 (484)	16 (219)	35 (232)	–	–	–	–
Underreport results	–	–	–	–	–	67 (871)	64
Sample selectively	56 (490)	53 (221)	22 (232)	37	51	29 (806)	23
Exclude data selectively	38 (484)	40 (219)	20 (232)	24	24	25 (806)	34
Drop covariates selectively	–	–	–	–	–	42 (773)	46
Switch analysis selectively	–	–	–	–	–	50% (811)	45
HARK	27 (489)	37 (219)	9 (232)	49	54	46 (880)	46
Round p-values	22 (499)	22 (221)	18 (232)	27	18	29 (806)	24
Mislead about demographic effects	3 (499)	3 (223)	4 (232)	–	–	–	–
Hide problems	–	–	–	–	–	24 (889)	–
Hide imputation	1(495)	2 (220)	1 (232)	5	2	10 (898)	9
Preregister study	–	–	–	–	–	54 (873)	47
Share data	–	–	–	–	–	46 (888)	64
Share code	–	–	–	–	–	59 (884)	–
Attempt replication	–	–	–	–	–	43 (876)	58
Post article publicly	–	–	–	–	–	78 (881)	85

Percentage of respondents saying they used the practice at least once (n). ¹The specific questions used varied slightly across studies. See the supplementary materials for all differences (<https://osf.io/wm7aq/>). ²The estimates from John et al. (2012) are those not using their manipulation designed to glean more candid responses. ³The studies of psychologists have focused on different countries: John et al. (2012) surveyed US psychologists, Agnoli et al. (2017) surveyed Italian psychologists, and Rabelo et al. (2020) surveyed Brazilian psychologists. For a table that includes our results in criminology, see (<https://osf.io/kj3bf/>)

p -values among the significant results in the literature to what would be expected if the results were all true positives. Simonsohn and colleagues (2014) compared studies with no obvious *indicia* of QRPs to psychology studies reporting results only with covariates (indicating potential selective use of covariates, a QRP) and found the latter contained excess p -values close to 0.05 and too few p -values close to zero. This is consistent with the pattern we would expect if covariates are reported selectively when they help produce significant results (i.e., a QRP), though other explanations, such as fraud, are also possible. Brodeur et al. (2020) reported similar findings in their analysis of articles published in 25 leading economic journals. They also found that studies using methods that give researchers more methodological discretion, such as instrumental variable analysis, showed more extensive evidence of p -hacking.

Another method for estimating the prevalence of QRPs is to use anonymous surveys to measure self-reported QRP use. Results from such surveys have been published for other disciplines (e.g., psychology, education, ecology) and for multiple regions (Italy, Brazil, US). John et al. (2012), for example, found that over 90% of US psychologists admitted to using at least one QRP. Multiple studies have asked about identical or very similar QRPs to each other (see a comparison of these studies' methods, <https://osf.io/wm7aq/>), making it possible to draw broad comparisons across fields. Table 1 lists the comparable results from seven prior studies (and we will compare our results to theirs in the forthcoming sections). A clear takeaway is that QRPs are common in many fields, with most QRPs being used, according to self-reports, by more than 20% of scientists, and some being used by the majority of scientists. To illustrate, 45% of US psychologists and 62% of education researchers self-report that they file drawer studies with null results (John et al. 2012; Makel et al. 2021). Similarly, most past surveys found that over 30% of scientists self-report HARKing (hypothesizing after the results are known) and over 20% self-report selectively rounding p -values. Depending on the discipline, 22–58% of scientists self-report data peeking with optional stopping (deciding whether to stop collecting data after looking at p -values), and 20–43% self-report that they exclude data selectively after looking at how the exclusion affects the results.

The Credibility Revolution and Open Science Practices (OSPs)

The threat posed by QRPs has been discussed most extensively in the field of psychology, arguably the eye of the storm of the “replication crisis.” In the wake of the “False Positive Psychology” paper (Simmons et al. 2011), Daryl Bem's paper claiming to find evidence of Extra Sensory Perception (ESP; Bem 2011), and several cases of fraud, the field of psychology entered a period of intense self-examination. The outcome has been a large and growing movement pushing for more attention to the quality and rigor of research, and faster progress on raising standards (Fidler and Wilcox 2018). This loosely-defined movement has been called a “credibility revolution” (Vazire 2018; see also Spellman 2015; Nelson et al. 2018).

In response to that movement, several large-scale replication projects have been conducted in the social sciences (Camerer et al. 2016; Camerer et al. 2018; OSC 2015; Ebersole et al. 2016; Klein et al. 2014; Klein et al. 2018a, b). Overall, the rate of “successful” replication (defined as any statistically significant effect in the same direction as the original, which is a fairly liberal criterion in most of these projects as they often had high statistical power to detect effects even much smaller than the original effect) is around 45%. Given that over 90% of published studies in the social sciences claim to find a positive (i.e.,

statistically significant) key result, this suggests that there are a lot of false positives in the published literature (Scheel et al. 2020). Another key finding from large-scale replications is that effect sizes in published articles tend to be substantially inflated (Kvarven et al. 2020). Camerer et al. (2018, p. 637), for example, replicated 21 social science experiments published in *Nature* and *Science* and found that “the effect size of the replications is on average about 50% of the original effect size.” The most likely culprit is QRPs.

Registered Reports, articles that are reviewed and accepted (or rejected) by journals before the data have been collected, are designed to reduce or eliminate avenues for QRPs. Journals cannot decide whether or not to accept a manuscript based on how exciting the results are, and authors cannot change their plan for data collection or analysis after the plan is approved (nor do they have much incentive to do so, if the manuscript has already been accepted for publication) (Ritchie 2020). Two different analyses comparing the results of Registered Reports to those of traditional journal articles (Allen and Mehler 2019; Scheel et al. 2020) both find that only about 45% of Registered Reports present a positive (i.e., statistically significant) key finding, compared to over 90% of traditional articles. This strongly suggests that QRPs account for much of the false positives in the traditional literature (though there are alternative explanations, e.g., that research hypotheses tested in Registered Reports have lower prior probabilities).

As a response to QRPs and related concerns about the credibility of research findings, researchers have proposed greater use of OSPs (Simmons et al. 2011, 1362–63), among other reforms (Vazire et al. 2020). These practices include the sharing of data and code, as well as preregistration, replication, and efforts to make articles themselves publicly available. Open practices make it easier to scrutinize a finding, for example by attempting to replicate the study (i.e., collect new data following the same procedures) or attempting to reproduce the results (i.e., re-analyze the original data). Of course, openness does not guarantee that findings will be robust; openness, rather, makes it easier to assess robustness. Critical appraisal is then necessary to identify robust versus weak results (Vazire and Holcombe 2020). Together, transparency and critical appraisal can curb the use of QRPs by incentivizing rigorous practices and deterring practices that inflate, exaggerate, or increase the risk of false positives.

Open practices also increase the probability that honest errors in research are uncovered. Research consistently finds that honest statistical errors are quite common (Ritchie 2020). In psychology, for instance, about 50% of published articles were flagged by the statcheck program as containing a statistical error (i.e., an inconsistency among the statistics reported within a single test), and about 12% were flagged as containing an error that changed the statistical significance of the result (Nuijten et al. 2016; see also Bakker and Wicherts 2011). In order for a field to be credible, it must make its errors detectable and incentivize the actual detection and correction of those errors (Vazire and Holcombe 2020). OSPs indicate a commitment to self-correction and are a hallmark of credible science.

The good news is that in the wake of the credibility revolution, researchers appear to be adopting OSPs. For instance, a recent study asked researchers in psychology, economics, political science, and sociology about the first time they had used one of three open practices: open data, open research materials, and preregistration (Christensen et al. 2019). Overall, they found considerable upticks in these practices over recent years. Similarly, journal policies encouraging or requiring open data seem to be having the desired effect, with articles published in those journals being more likely to have made their data available in a public repository (Hardwicke et al. 2018; Kidwell et al. 2016; c.f., Rowhani-Farid and Barnett 2018). Unfortunately, the evidence on the prevalence of OSPs in different fields is still scant. In Table 1, we list estimates from two prior studies (from education

and quantitative communication). Both found that posting public copies of articles was the most common open practice and that about half of respondents had shared data and/or analysis code.

Application to Criminological Research

Criminology should be just as concerned as other fields about avoiding QRPs and ensuring research is credible, especially given the societal implications of its findings. As Gelman et al. (2020, p. 296) explain, “criminological research findings have considerable potential to influence (for better or worse) citizens’ lives, given the immense reach of the criminal justice system.” Indeed, there is a growing movement toward a “public criminology,” or, in other words, research that is useful to the individuals, communities, and social and governmental institutions (Uggen and Inderbitzin 2010). Beyond informing policy and other social interventions, criminological research is also relied on in courts. For example, QRPs were used by a criminologist who studied gangs in the wrongful conviction of a young man in Ontario (Chin 2018; Chin et al. 2019). That criminologist’s use of analytical flexibility (e.g., a shifting definition of “gang member” across studies) resulted in an overstatement of the evidence suggesting that a certain tattoo indicated the bearer was involved in a gang killing.

Despite progress and meta-research in other fields, levels of use and endorsement of QRPs and OSPs among criminologists remain unclear. Usefully, however, one recent study of 75 terrorism researchers found evidence that they supported the use of OSPs, although, unfortunately, they rarely used them (Schumann et al. 2019). And a recent scandal in the field suggests that even among co-authors, data and code are not always shared (Pickett 2020). This may be exacerbated by disciplinary norms – for example, no criminology journal (to our knowledge) requires the sharing of data or code.

Lack of OSP use is unfortunate because they produce demonstrable benefits (Allen and Mehler 2019). For instance, in one study of the effects of police violence, open data allowed a reader to find a coding error that changed the study’s main finding (American Association for the Advancement of Science, 2019). The author retracted the study before it could have downstream effects. Moreover, OSPs make it easier to conduct replications, which are a cornerstone of scientific knowledge, and are also exceedingly rare in criminology, constituting 0.5–2% of published articles depending on the definition of replication (Pridemore et al. 2018; McNeeley and Warner 2015). Finally, OSPs make it harder to use QRPs, because many QRPs are, by definition, about withholding relevant information from readers.

Study Overview

To provide initial evidence about how criminologists view QRPs and OSPs, and about whether they use them, we conducted a preregistered study of researchers who publish criminological science. The population of interest for our study was researchers who published in criminology and criminal justice journals during the past 10 years. Our study, the first survey research on QRPs and OSPs in criminology, can be used to shed light on whether there are particular strengths and weaknesses in criminology’s current practices. The findings can also be used as benchmarks to be revisited as the field changes. As we will describe, we asked participants about 10 QRPs (Table 3) that have been widely studied elsewhere, which include two that border on research fraud (filling in missing data without

reporting it and hiding known problems with the data) and 5 OSPs recently studied in surveys of education (Makel et al. 2021) and communication (Bakker et al. 2020) researchers.

As stated in our preregistration (<https://osf.io/fbhkq>), our study's primary aim was descriptive. Specifically, we aimed to provide estimates of criminologists' self-reported use of the 10 QRPs and 5 OSPs examined ("use"), their perceptions of other criminologists' use of these practices ("prevalence"), and their levels of endorsement of these practices ("support"). We also specified two hypotheses in advance of data collection. Our first hypothesis was that use of and support for QRPs would be negatively correlated with use of and support for OSPs. This hypothesis flows from a deterrence theory of open practices; they arose, in part, to make transparent, and therefore discourage, QRP use (Simmons et al. 2011, 1362–63). Our second hypothesis was that methodological training would be associated with use of and support for both QRPs and OSPs, independent of career stage. Training might make researchers more aware of the negative effects of QRPs (and benefits of OSPs). Alternatively, QRP use could be enabled by greater methodological knowledge and skill. Given the effect of training could plausibly go in either direction, we refrained from making a directional hypothesis.

Methodology

Sample

Our research design follows those used to study QRPs and OSPs in other fields (Table 1). Our materials and de-identified data are publicly available in the Open Science Framework (OSF) repository (<https://osf.io/qvcdg/>). Our study received human ethics approval from the University of Sydney (<https://osf.io/n5svq/>). We used a computerized, self-administered survey because research suggests that it is the best mode for obtaining honest answers (Tourangeau et al. 2013).

Our population of interest was active researchers in criminology, defined as researchers who had published at least one article in a criminology or criminal justice journal in the previous 10 years. Defining the population of interest this way is similar to Fraser et al. (2018), Makel et al. (2021), and Bakker et al. (2020), who also surveyed researchers who had published in journals in their field(s) of interest. We selected criminology journals using the Web of Science's "Criminology and Penology" category (Web of Science 2018) and two academic studies of criminology journals (DeJong and St. George 2018; Sorenson 2009). From these lists, we excluded 23 journals we determined were not sufficiently related to criminology (e.g., *Journal of Forensic Psychiatry & Psychology*), and 14 journals for other reasons (e.g., language other than English). As a result, we sampled from 67 criminology journals. This process and exclusion justifications were detailed in our preregistration (<https://osf.io/fbhkq>). They are further explained in our supplementary materials (<https://osf.io/myhx9/>).

From the 67 journals, we extracted 16,157 unique author email addresses. For journals indexed by the Web of Science, we obtained emails through its database of article information. For others, we adapted code written by Makel et al. (<https://osf.io/83mwk/>) that scrapes journal websites for e-mail addresses (<https://osf.io/qvcdg/>). In some cases, we also obtained email addresses by hand-coding author information (<https://osf.io/myhx9/>). Survey invitations and follow-up reminders were sent on August 10, 20, and 28, 2020. We closed data collection on September 12, 2020. Of the 16,157 obtained email addresses,

17 failed, and 2,370 bounced back, resulting in a total of 13,770 successful email account contacts. However, some of those accounts may not have been actively monitored by their owners during the time period of our survey (August, 2020) because, for instance, some may have retired.

In total, we received 1,612 responses. This response rate (12%) is small, but similar to other recent studies sampling authors or editors (Makel et al. 2021; Hopp and Hoover 2017; Horbach and Halfman 2020), and exceeds those often obtained by professional polling organizations (Keeter et al. 2017). A large body of research shows that “nonresponse bias is rarely notably related to [the] nonresponse rate” (Krosnick et al. 2015, p. 6). However, in our survey, given its topic (research behavior), nonresponse may have resulted in bias. Any nonresponse bias, however, is likely to result in underestimates of QRP use and support, and in overestimates of OSP use and support, because, if anything, support for the credibility revolution would likely have increased individuals’ likelihood of responding to our survey.

As in Makel et al. (2021), we asked respondents at the start of the survey: “Have you conducted quantitative research that involves null-hypothesis significance testing?” Unlike Makel et al. (2021), we excluded from our main report those who reported they did not do quantitative research involving null-hypothesis significance testing ($n=479$), because they were not asked all of the questions (they were asked about: HARKing, underreporting results, hiding data problems, hiding imputation and all the OSPs). This exclusion is not listed in our preregistration because we did not anticipate the difficulties created by only asking a subset of the questions to the subsample of non-quantitative respondents. After collecting the data, but before looking at the results, we decided it would increase comparability to limit the analysis to respondents who received the same questionnaire. However, the data for all respondents, quantitative and non-quantitative, is provided online in the supplementary materials (<https://osf.io/8me9w/>) and, where possible, the analyses below have been reproduced on the whole dataset and on the non-quantitative sample.¹

Another 50 respondents are excluded because they indicated they did not want their data used. Finally, there was item non-response, which further reduced the full analytic sample to between 579 and 711, depending on the analysis.² To provide a better idea of the composition of our sample, Table 2 breaks down respondents’ career level and the number of statistics and methods courses they reported having taken. As can be seen, our sample was predominantly mid-career and senior researchers with a high degree of methods or statistical training. The modal categories in our sample were senior researchers who had taken ten or more methods courses—an important subsection of quantitative criminologists who are likely to publish regularly and to be influential in the discipline. (Details on the non-quantitative sample are included in the supplementary materials.)

Measures

We asked participants about 10 QRPs (Table 3) that were also included in prior surveys in other fields (Table 1). These practices likely vary in the degree to which we would expect the community to proscribe them. For instance, it is easier to construct innocent

¹ <https://github.com/alexholcombe/ChinHolcombePickettVazireCrimSurvey/>.

² Randomization of question ordering (see below) meant that breakoffs equally (on expectation) affected all practices, but also meant that item nonresponse was not concentrated at the end of the survey. As a result, there are many respondents who answered questions about only one randomly presented QRP or OSP.

Table 2 Career stage and methods training of our sample

Stage	n	Percentage
Career level of respondents		
Graduate student	32	5
ECR	158	25
Mid-career	199	32
Senior	241	38
Number of classes	n	Percentage
Methods or stats classes taken		
0	5	1
1	10	2
2	30	5
3	42	7
4	83	13
5	99	16
6	80	13
7	54	9
8	58	9
9	15	2
10+	151	24

Participants self-reported their career level and the number of methods or statistics classes they had taken. These questions were asked at the end of the survey. For career level, the exact response options were: Graduate student; Earlier career academic/researcher (including post-doctoral fellows); Mid-career academic/researcher; Senior research academic/researcher. For classes taken they were asked, “How many university courses (undergraduate or graduate) on methodology or statistics have you taken?” and given the options in the Table

explanations for rounding down p -values (e.g., 0.054–0.05) than filling in missing data. We also asked about five OSPs (Table 4) that Makel and colleagues (2021) included in their survey. The order of the presented practices was randomized between participants. Tables 3 and 4 provide the exact question wording for the specific QRPs and OSPs, along with the abbreviations (variable names) that we use in the figures. For each practice, as in prior research, we measured self-reported use, perceived prevalence, and support.

Use was measured with two questions. The first asked: “Have you ever engaged in this practice?” (1 = yes, 0 = no). The second was a contingency question asked to those who answered affirmatively to the first question: “What PERCENT of studies you have conducted—that is, how many out of 100—would you say that you used this practice?” In the descriptive analysis, we separately analyzed responses to these two behavioral questions, but for the correlational analysis we combined them by coding respondents who reported not doing the practice as “0%” on the percent of studies variable. Perceived prevalence was measured with the question: “What percent of criminologists—that is how many out of 100—would you say have engaged in this practice on at least one occasion?” Finally, support for the practice was measured by asking: “How frequently SHOULD criminologists

Table 3 Questionable research practices (QRPs): question wording and self-reported use among quantitative criminologists

QRP	Percentage using		For users, percentage of studies using		N
	Estimate	95% CI	Estimate	95% CI ³	
HARK	29%	25–32%	36%	31–40%	686
Underreport Results	53%	50–57%	47%	44–51%	677
Hide Problems	10%	8–12%	31%	23–39%	696
Hide Imputation	7%	5–9%	34%	24–44%	683
Omit non-significant studies or variables	43%	40–47%	34%	31–38%	681
Drop Covariates Selectively	32%	28–35%	39%	35–44%	670
Round P-Values	27%	23–30%	46%	40–51%	692
Exclude Data Selectively	24%	20–27%	34%	29–39%	679
Sample Selectively	15%	12–18%	29%	23–34%	680
Switch Analysis Selectively	39%	35–42%	29%	25–32%	681
Used Any QRP ¹	87%	84–89%	–	–	711
Total QRPs Used (mean) ²	2.7	2.6–2.9	–	–	579

¹Among Respondents who answered at least three QRP questions. ²Among Respondents who answered all QRP questions. ³CI's calculated as $-/+1.96*(sd/(\sqrt{n}))$

Table 4 Open science practices (OSPs): question wording and self-reported use among quantitative criminologists

OSP	Percentage using		For users, percentage of studies using		N
	Estimate	95% CI	Estimate	95% CI ²	
Preregister Study	45%	42–49%	50%	45–54%	680
	“Preregistering hypotheses and analysis plans prior to data collection.”				
Share Data	43%	40–47%	34%	31–37%	689
	“Sharing data you collected to a publicly accessible, online repository.”				
Share Code	43%	40–47%	32%	29–35%	683
	“Sharing code or other research materials to a publicly accessible, online repository.”				
Attempt Replication	40%	37–44%	21%	18–24%	688
	“Sought to replicate the work of other researchers by following their methods as closely as possible with no intentional changes.”				
Post Article Publicly	68%	65–72%	59%	56–62%	680
	“Posted copies of your research so that it is not behind a paywall (e.g., on a publicly accessible, online preprint server).”				
Used Any OSP ¹	89%	87–91%	–	–	682
Total OSPs Used (mean) ²	2.4	2.3–2.5	–	–	597

¹Among Respondents who answered at least three OSP questions. ²Among Respondents who answered all OSP questions. ²CI_s calculated as $-1 + 1.96 * (sd / \sqrt{n})$

use this practice?” There were four response options: Almost always (coded 4), often (3), rarely (2), and never (1).³

To maintain respondents’ anonymity, we asked only two background questions. The first assessed their career stage: “Which of the following best describes your current position?” There were four response options: Senior research academic/researcher (coded 4), mid-career academic/researcher (3), earlier career academic/researcher (including post-doctoral fellows) (2), and graduate student (1). The second question measured methodological training: “How many university courses (undergraduate or graduate) on methodology or statistics have you taken?” There were eleven numerical response options, ranging from “0” to “10 or more.”

Analytic Strategy

As described in our preregistration (<https://osf.io/fbhkq>), most of our analyses are descriptive, examining the distribution of responses to the individual questions about each practice. For the analyses examining associations among variables, we constructed mean indices, retaining only those respondents who answered at least three of the component items in the respective index. To do this, we dropped respondents who answered two items or less, and then, for the remaining respondents, averaged their responses across the 3–10 (for QRPs) or 3–5 (for OSPs) items they answered. The measurement precision of the

³ In using the 0–100% response scale, our assumption was that criminologists would be as able to use it as laypeople, who regularly respond on this scale in major surveys (Manski 2004).

constructed indices thus depends on the number of items answered, and respondents who answered fewer items will have larger variance.⁴ In our preregistration, we did not specify the item-missingness criterion we would use to construct the mean indices. However, prior to looking at the results, we decided to create the indices only for respondents who answered at least three of the component items.

These indices were used in correlations and in ordinary least squares regressions, where we also use robust standard errors to account for heteroskedasticity. The linear regression equation was as follows:

$$Y_i = \alpha + \beta_1(\text{Career Stage})_i + \beta_2(\text{Methods Training})_i + \varepsilon_i$$

This also represented a deviation from our preregistration, which planned to use negative binomial and ordered logistic regression, based on assumptions about the distribution of the outcomes. However, all of the outcomes are functionally continuous (see [Appendix](#)).⁵ Because of these departures from our analysis plan, we urge caution in interpreting the findings.

Results

Questionable Research Practices (QRPs)

Use of QRPs

How many criminologists report using QRPs? Table 3 presents the self-reported use of QRPs among quantitative criminologists during their career (see the supplementary materials for a comparison of criminologists to other fields). Use of specific QRPs ranged from 7 to 53% (see Table 3 for 95% confidence intervals around all point estimates reported here). The most commonly used QRPs were: failing to reported the full set of conducted analyses (underreport results, 53%), failing to report null results (omit non-significant studies or variables, 43%), changing the analysis after an earlier one failed to yield significant findings (switch analysis selectively, 39%), using *p*-values to select covariates (drop covariates selectively, 32%), hypothesizing after the results are known (HARK, 29%), and excluding data after checking how it impacts results (exclude data selectively, 24%).

It is concerning that 7% of respondents, by their own admission, do not always disclose when they impute (fill in) missing values, given that it is arguably a form of data fraud if it is unreported—specifically, falsification of data (see Fraser et al. 2018, p. 5). Although multiple imputation is widely used and often appropriate, the procedure should be declared (see Carpenter and Kenward 2012). About 10% of respondents admitted to not disclosing known problems with the method, data, or analysis that potentially impact conclusions (hide data problems).

The QRP responses were combined into a summary index for each participant. Respondents were free to leave any question blank, however, and many respondents did not answer every QRP question. Among those that answered at least three QRP questions,

⁴ Because this may bias the coefficients toward 0, such that estimates are underestimates, we estimated supplementary models using only those respondents with complete data on the indices. The findings were the same.

⁵ The findings are the same when negative binomial regression is used for the outcome variables measuring usage.

the majority (87%) admitted using at least one QRP. Among respondents who answered every QRP question, the average number of QRPs used was three. These metrics were not preregistered, although they are commonly reported in research on QRPs (John et al. 2012; O'Boyle et al. 2017). Overall, the findings indicate that most respondents have used QRPs and that the average respondent has used more than one. Respondents who reported using QRPs also tended to report using them repeatedly. Specifically, QRP-using respondents reported using the different QRPs in 29% to 47% of their studies. Even for the two most serious QRPs (hiding known data problems and filling in missing values without reporting it), users reported regular use (on average, in 31% and 34% of studies, respectively).

It is instructive to compare QRP use in criminology (Table 3) to that in other fields (Table 1; Supplementary materials, <https://osf.io/kj3bf/>), although this comparison should be considered only suggestive because these studies were conducted in different times and countries, and used different sampling methods and question wording (in some cases). Our findings for criminologists are generally in line with those from studies in other disciplines. For example, John et al. (2012) found that 91% of psychologists admitted using at least one QRP, whereas 87% of criminologists admitted doing so in our study. Turning to specific QRPs, 1–10% of scientists in other fields said they changed data without reporting it (hide imputation), compared to 7% of criminologists in our sample. Similarly, 40–62% of scientists in other disciplines said they failed to publish studies with null findings; the figure is 43% for criminologists in our sample. In other disciplines, 20–43% of scientists decided whether to exclude data after looking to see how it affected results, a range that includes our prevalence estimate for criminology (24%). The most notable difference between our results and those of other studies is for selective sampling (using *p*-values to decide when to stop data collection). Comparatively few criminologists in our sample (15% vs. 22–58% in other disciplines) use this QRP. This finding may reflect a greater reliance on secondary data among criminologists, which would reduce their opportunities for selective sampling.

Perceived Prevalence of QRPs

Do criminologists believe that QRPs are common? Perceived prevalence was measured by asking respondents what percent (0–100) of criminologists they would say have engaged in the practice at least once. Figure 1 shows respondents' perceptions of prevalence for each QRP. Respondents perceive a relatively high prevalence of QRPs among other criminologists. Respondents perceive that 21–59% of other criminologists have used each QRP at least once (medians: 10% to 60%). Thus, not only have most criminologists in our sample used QRPs, but most also believe that many other criminologists use them (see our supplementary materials for a comparison of self-use of QRPs to perceived prevalence, <https://osf.io/7mjpd/>).

In general, the pattern of perceived prevalence across QRPs is similar to the pattern of self-reported use, with hiding data problems, hiding imputed data, and selective sampling perceived as relatively rare, whereas omitting non-significant studies or variables, under-reporting results, and selectively switching analyses perceived as most common. However, this similarity between the pattern of mean self-reported use and the mean perceived prevalence may be misleading. Figure 1 shows that the distribution of participants' responses to some of the prevalence questions resembles a uniform distribution. That is, for some of the practices, the reason the mean prevalence response is close to 50% is not because

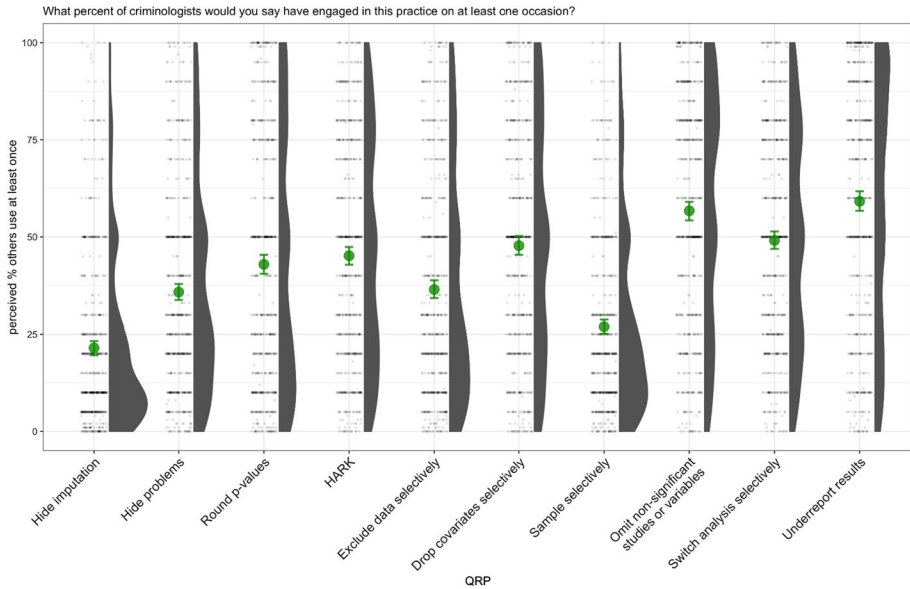


Fig. 1 Perceived Prevalence of QRPs. *Notes:* Distribution of the perceived % of other researchers using the QRP at least once. Individual responses are plotted in grey, and the density is plotted in dark grey. The mean is plotted in green, with 95% confidence intervals calculated using the percentile bootstrapping method (Efron & Tibshirani, 1994)

50% was a typical answer, but rather because participants gave answers nearly uniformly distributed throughout almost the entire range. This suggests that most participants know very little about the prevalence of these practices in their field. One possibility is that they have a good estimate of the prevalence among some of their peers, but not the field as a whole, and these peer communities are very heterogeneous. As we will elaborate on in the discussion, we obtained data from six previous QRP studies and found a similar pattern of results, suggesting that descriptive norms about research behavior may be weak and only weakly tied to reality.

Support for QRPs

Do criminologists believe QRPs are defensible? Fig. 2 shows the distribution of respondents' answers, ordered from those with the least support (highest proportion of "never" answers) to the most support. Most respondents support using some QRPs in some circumstances.⁶ For example, 67% of respondents support (in at least some circumstances) selectively choosing not to publish null findings (omit non-significant studies or variables), 65% support looking at p -values before deciding whether to collect more data (sample selectively), and 45% support framing unexpected findings as if they were hypothesized a priori (HARK) (see Fig. 2). Perhaps most concerning is that 25% of respondents believe it can (even if rarely) be okay to hide known data problems, and 18% of respondents say it can be okay to fill in missing values without disclosing it to readers. Unlike the use questions,

⁶ We define support as any answer other than "never."

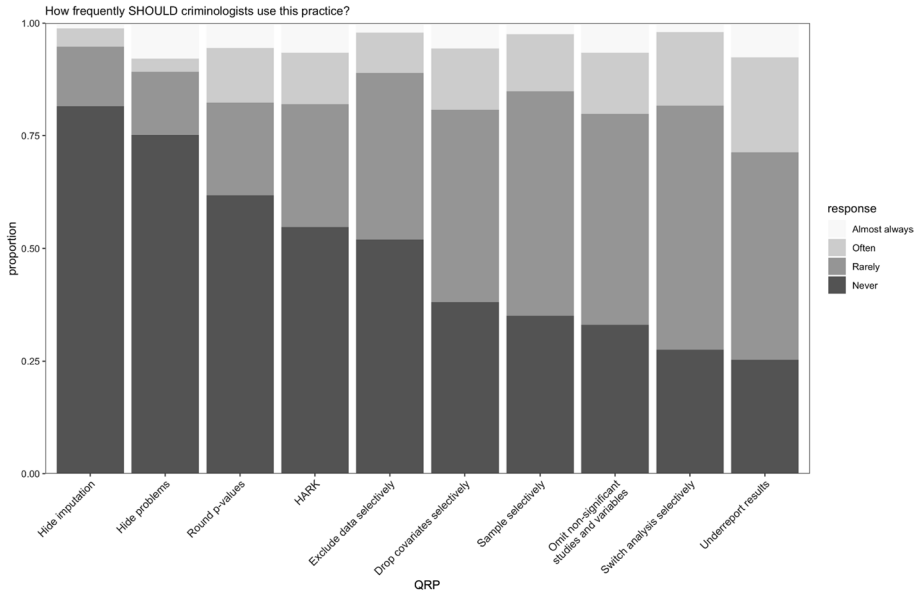


Fig. 2 Support for QRPs. *Notes:* Participants reported whether they thought the stated practice should be used never, rarely, often, or almost always

which may capture behavior from years ago, the support questions measure criminologists' current support.

Open Science Practices (OSPs)

Use of OSPs

How widespread is OSP use in criminology? One might assume that if QRPs are common in criminology, then OSPs would not be, but prior research suggests this may not be the case. Makel et al. (2021), for example, found that both QRPs and OSPs were common in education research, with most scientists using both. Is the same true of criminologists? Table 4 displays the five OSPs we asked about and the percentage of researchers saying they had used them at least once, and among those, the percentage of studies they had used them in.

Our findings mirror those of Makel et al. (2021) and Bakker et al. (2020) (Table 1; Table 4). They found that the most common OSP was posting articles publicly, so that they are not behind a paywall, with 78% of education researchers and 85% of communication researchers using this practice. The same is true in our survey of criminology, where 68% of respondents have posted articles publicly. Previous studies also found high levels of preregistration (54% in education, 47% in communication), data sharing (59% in education, 64% in communication), and attempting a replication (43% in education, 58% in communication). A further 59% in education reported sharing code at least once (the communication study did not ask about code). The numbers in our survey are similar, although in every case they are lower (we did not perform any inferential statistics): 45% of respondents said they have preregistered studies, 43% have shared data, 40% have attempted a replication,

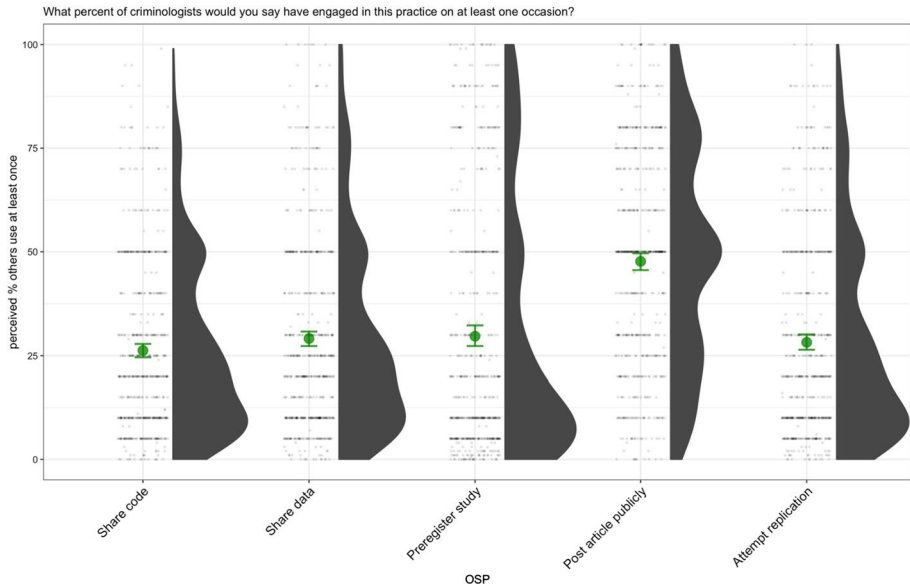


Fig. 3 Perceived Prevalence of OSPs. *Notes:* Distribution of the perceived % of other researchers using the QRP at least once. Individual responses are plotted in grey, and the density is plotted in dark grey. The mean is plotted in green, with 95% confidence intervals calculated using the percentile bootstrapping method (Efron & Tibshirani, 1994)

and 43% have shared code. It bears noting that if 40% of criminologists have attempted replications, then the finding in prior research that only 0.5–2% of published criminology articles are replications (Pridemore et al. 2018; McNeeley and Warner 2015) suggests there may be a large unpublished replication literature in the discipline (there may also be differences in how our respondents defined replication, see the discussion). Overall, 89% of the respondents who answered at least three OSP questions said they had used at least one OSP. Among those who answered all the OSP questions, the average respondent reported using two OSPs.

Additionally, respondents who have used OSPs have, on average, used them frequently (for about 20–60% of their studies, depending on the practice). For instance, those who have posted articles publicly have done so for most (59%) of their studies. Those who have preregistered studies have done so for half (50%) of their studies. Those who have shared data and code have done so for about a third of their studies. It is notable that the vast majority of quantitative criminologists in our sample have used OSPs (89%) and used them frequently, but a similarly large majority have also used QRPs (87%). Although this may seem contradictory, because OSPs signal transparency whereas many QRPs involve hiding crucial information from readers, there are several possible explanations, which we will discuss in the conclusion.

Perceived Prevalence of OSPs

Do criminologists believe that OSPs are common in the discipline? Fig. 3 shows respondents' perceptions of the percentage of other criminologists who have used each

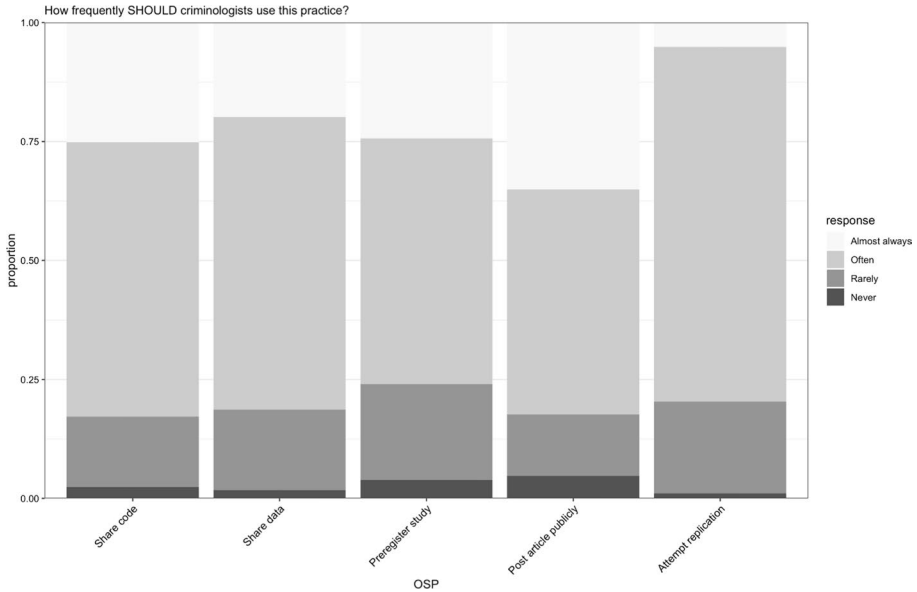


Fig. 4 Support for OSPs. *Notes:* Participants reported whether they thought the stated practice should be used never, rarely, often, or almost always

OSP at least once. The perceived prevalence of OSPs is around 26–30% for most OSPs (medians = 15–25%), but somewhat higher (48%, median = 50%) for posting articles publicly. Each distribution has a fairly prominent peak, suggesting more agreement (or knowledge) about the prevalence of OSPs than QRPs, which makes sense given that OSPs are public but QRPs are hidden. On average, respondents seem to perceive OSPs as slightly less prevalent than QRPs. As with QRPs, the pattern of perceived prevalence across OSPs matches the pattern of self-reported use, with posting articles publicly perceived as more prevalent than the other OSPs.

Support for OSPs

Do criminologists support the use of OSPs? Recall that the response options for the support question (“How frequently should criminologists use this practice?”) were “never”, “rarely”, “often”, and “almost always”. Figure 4 shows the distribution of respondents’ answers. The findings are striking. Respondents are *much* more supportive of OSPs than of QRPs. For each OSP, more than 75% of respondents reported that OSPs should be used “often” or “almost always,” and over 95% supported their use at least “rarely”. There is evidently a strong consensus in criminology that OSPs are important and should be used. However, there are also some sobering patterns in the results. For example, for sharing code or posting articles publicly, which seem to us to be universally good practices (i.e., we cannot think of cases where these would be harmful), only about 25–35% of respondents selected “almost always”. Another striking

Table 5 Correlation Matrix

Variables	1	2	3	4	5	6	7
1. Career Stage	–						
2. Methods Training	–.04	–					
3. Personal QRP Usage ¹	.04	–.03	–				
4. Personal OSP Usage ¹	.07	.04	.21*	–			
5. Support QRP ¹	.12	–.03	.56*	.09	–		
6. Support OSP ¹	–.09	.07	–.01	.40*	–.15*	–	
7. Perceived QRP ¹	–.17*	.07	.44*	.11	.28*	.18*	–
8. Perceived OSP ¹	–.02	–.01	.18*	.42*	.15*	.10	.22*

¹Variable is a mean index calculated for respondents who answered at least three of the items

* $p < .05$ (two-tailed, Bonferroni-corrected)

pattern is that 99% of respondents said that criminologists should at least sometimes (even if “rarely”) attempt replications, but this OSP had the lowest rate of self-reported use (40%, Table 4).

Correlations Between QRP and OSP Responses

Table 5 presents the bivariate correlations among the variables. Interestingly, and contradicting our first hypothesis, we find a significant and positive correlation between QRP and OSP use ($r[667] = 0.21$, $p < 0.001$, 95% CI = 0.14–0.29), though note that we preregistered a one-tailed test in the opposite direction, so this finding should be considered exploratory, albeit quite strong. This correlation is descriptively larger than the small positive correlation ($r = 0.06$) found by Makel et al. (2021) among education researchers. Similar to Makel et al. (2021), however, and consistent with the part of our first hypothesis having to do with support, we find a significant and negative correlation ($r[661] = -0.15$, $p < 0.001$, 95% CI = -0.22 to -0.07) between support for QRPs and support for OSPs. The comparable correlation in Makel et al. (2021) was $r = -0.20$. In sum, we find mixed evidence for our first hypothesis. While there is some consistency in support (more support for OSPs is associated with less support for QRPs), behavior appears to be inconsistent—respondents who have used more QRPs have also used more OSPs. This is somewhat counterintuitive as OSPs increase transparency whereas most QRPs involve obfuscation or hiding information.

Methodological Training, Career Stage, and Research Practices

Turning to our second hypothesis, Table 6 presents the relevant regression results. We find no evidence that methodological training is significantly related to either research behavior or attitudes, which runs contrary to our hypotheses (Table 6). Controlling for career stage, the relationship of methodological training to QRP use is small and non-significant ($b = -0.123$, $p = 0.453$, 95% CI = -0.445 to 0.199), as is its relationship to OSP use ($b = 0.228$, $p = 0.328$, 95% CI = -0.229 to 0.684).⁷ Similarly, the relationship

⁷ CIs calculated as $-/+1.96*(sd/(sqrt(n)))$.

Table 6 Regressions predicting quantitative criminologists' perceptions and use of questionable research practices and open science practices

Variables	Model 1: Support QRPs		Model 2: Support OSPs	
	<i>b</i>	SE	<i>b</i>	SE
Career Stage	.055**	.018	-.040*	.017
Methods Training	-.005	.006	.011	.007
N	622		614	
Variables	Model 3: Perceived QRPs		Model 4: Perceived OSPs	
	<i>B</i>	SE	<i>b</i>	SE
Career stage	-3.309***	.800	-.373	.673
Methods training	.425	.267	-.057	.237
N	585		582	
Variables	Model 5: QRP Usage		Model 6: OSP Usage	
	<i>b</i>	SE	<i>B</i>	SE
Career stage	.496	.450	1.164	.681
Methods training	-.123	.164	.228	.232
N	624		615	

Models are estimated using ordinary least squares regression with robust standard errors

* $p < .05$; ** $p < .01$, *** $p < .001$ (two-tailed)

between methodological training and support for QRPs and OSPs is small and non-significant (QRPs: $b = -0.005$, $p = 0.412$, 95% CI = -0.017 to 0.007 ; OSPs: $b = 0.011$, $p = 0.089$, 95% CI = -0.001 to 0.024). The confidence intervals in all results exclude unstandardized effects with absolute values greater than 0.7, suggesting that we have enough precision to confidently rule out any meaningfully-sized association between methodological training and responses to our QRP and OSP items.

We also examined the association between career stage and responses to QRP and OSP questions, with later career stages coded with higher scores. Like methodological training, career stage is not significantly related to QRP and OSP use (QRPs: $b = 0.496$, $p = 0.270$, 95% CI = -0.387 to 1.380 ; OSPs: $b = 1.164$, $p = 0.088$, 95% CI = -0.174 to 2.502). However, we do find some significant associations between career stage and QRP and OSP support. Compared to respondents at early career stages, those at later stages are: (1) significantly more supportive of QRPs ($b = 0.055$, $p = 0.003$, 95% CI = 0.019 to 0.091), (2) significantly less supportive of OSPs ($b = -0.040$, $p = 0.021$, 95% CI = -0.074 to -0.006), and (3) significantly less likely to perceive QRPs as common in the discipline ($b = -3.309$, $p < 0.001$, 95% CI = -4.880 to -1.738). All of these relationships remain significant using a Bonferroni-corrected alpha of 0.025 (to correct for the inclusion of two predictors in each of the models). We present these findings about career stage to flag them as potentially important and worthy of follow-up. However, they should be interpreted as exploratory because, while we did

preregister the use of career stage as a covariate in our models (<https://osf.io/fbhkq>), we did not predict a relationship between career stage and QRP or OSP support.

Discussion

We found widespread self-reported use of QRPs among criminologists at levels similar to what has been found for other fields. Criminologists also supported the use of most QRPs in at least some circumstances (Fig. 1), even though some of these practices entail hiding or misrepresenting information. Moreover, respondents estimated that others were more likely to use QRPs than they were themselves. As we discuss below, this pattern of results, and other design features of our study, suggest we may be underestimating the prevalence of QRP use (and overestimating the prevalence of OSP use).

The high rate of QRP usage is disappointing because QRPs contribute to false and misleading findings. Our evidence is consistent with the conclusion that many findings in criminology are likely false positives (Sweeten 2020; Gelman et al. 2020; Wooditch et al. 2020). Existing efforts to make criminologists aware of the pitfalls of QRPs (see Burt 2020) should be strengthened. Given the high rate of QRP use documented in our study, one important takeaway is that researchers seeking to draw conclusions from the criminological literature—for example, by conducting meta-analyses—should take into account the likely bias introduced by QRPs, using such procedures as *p*-curve or *p*-uniform (Simonsohn et al. 2014; van Assen et al. 2015). Many meta-analyses in criminology fail to take such biases into account (e.g., Wolfe and Lawson 2020), and those that do use outdated procedures to attempt to correct for these biases (e.g., Braga et al. 2014, 2018), such as trim-and-fill, which are known to be ineffective (Simonsohn et al. 2014; van Assen et al. 2015).

Based on our experience, we expected a lower level of self-reported adoption of OSPs among criminologists. Instead, the levels are in line with prior research in other disciplines (Makel et al. 2021). Our survey (and others in different fields) may overestimate OSP use, in part because it is likely seen as socially desirable behavior. In any event, it is promising that so many respondents report using OSPs and that nearly all support these practices. We were especially surprised by the high level of self-reported use of preregistration. Prior studies have found that preregistration lags other OSPs (Christensen et al. 2019), whereas we found it was used at similar rates as other OSPs. One explanation for this difference may be that some participants in our study interpreted preregistration more liberally than we intended (recall we asked about “preregistering hypotheses and analysis plans prior to data collection”). They may have taken this to mean recording research plans anywhere, such as in grant applications or in communications with collaborators. We suggest future studies should use a more specific and detailed definition of preregistration (e.g., specifying that the plan should be recorded in a time-stamped repository). Subsequent research should also ask whether criminologists adhere to their preregistrations, which we did not ask about; some research suggests they often do not (Wooditch et al. 2020).

Almost 70% of respondents reported publicly posting at least one article in their career, and those indicating they had done so reported doing it for about 60% of their studies. Although the prevalence of this OSP in criminology seems high, it is actually lower than

found in other disciplines (Bakker et al. 2020; Makel et al. 2021). However, despite this seemingly high rate, open access to criminology articles remains low. Ashby (2020) recently found that less than 25% of criminology articles published from 2017–2019 were available in open access format (despite all criminology journals he studied allowing pre-prints). The explanation for the discrepancy between his results and ours is unclear. It may be that our sample is overestimating their own pattern of publicly posting articles. It may be that articles posted publicly (e.g., on ResearchGate.net) were subsequently taken down, either by the website or the researcher. ResearchGate.net, for example, has removed many public full texts because of journal policies. Another possible explanation may be that our sample is overrepresenting criminologists who have used OSPs. Regardless, it is encouraging that 295 criminologists recently signed an open letter to the American Society of Criminology requesting that criminology journals allow authors to post full-text versions of their articles publicly.⁸

Contrary to our preregistered hypothesis, we did not find a negative relationship between QRP and OSP use; in fact, we found an unexpected positive relationship. As noted, this relationship should be interpreted with caution given that we preregistered a one-tailed test, though the result is quite strong even for an unexpected finding. This positive relationship runs contrary to a deterrence view of open practices, which suggests that the certainty of detection—presumably increased by OSPs—should deter deviance such as use of QRPs (Apel 2013). Therefore, OSPs may not be effective at deterring QRPs, though several other explanations are also plausible (see below). Some prior research does suggest that OSPs fail to deter QRPs. For example, all of the studies analyzed in Franco et al. (2014, 2015) were essentially preregistered through the TESS submission process, which also made both their preregistrations and data publicly available, and yet publication bias and other QRPs remained rampant. Theoretically, from a deterrence perspective, these findings suggest that OSPs may not affect the *perceived* certainty of detection, which is what drives decision-making (Apel 2013), even if they do influence the actual certainty of detection.

Of course, there are other factors that may be driving the positive relationship between QRPs and OSP. For example, it maybe that pro-OSP criminologists are more likely to be honest about their use of QRPs in the past. Alternatively, there may be an unmeasured common factor, such as research productivity, that is positively related to both QRPs and OSPs, distorting their true causal relationship, assuming there is one. Criminologists who publish more articles have more opportunities to use QRPs and OSPs, and thus may be more likely to use both practices. Another possibility is that the positive relationship between QRP and OSP use reflects selective transparency, whereby criminologists use both practices, but do so in different articles. It may be that criminologists who are more focused on their careers and prestige are more likely to use QRPs to get articles published in top journals. O’Boyle et al. (2017) found that QRPs were more common in articles published in top journals. However, the same career-oriented criminologists may capitalize on the reputational benefits of using OSPs when they can (e.g., when the first analyses run are significant). The evidence that criminologists deviate selectively from their preregistrations to increase effect sizes is consistent with this selective transparency explanation (Wooditch et al. 2020).

Although QRP and OSP use were positively related in our sample, the relationship between support for QRPs and OSPs was negative, as hypothesized. This negative correlation for attitudes was also found among education researchers (Makel et al. 2021). The finding indicates that those who endorse one set of practices are less likely to endorse the

⁸ <https://www.criminologyopen.com/pub/open-letter-to-asc-concerning-green-access-to-its-journals/release/21>.

other. Unlike behavior, which was measured retrospectively (“Have you ever engaged in this practice?”), attitudes were measured contemporaneously, at the time of the survey. Thus, the negative correlation between current support for QRPs and OSPs, combined with the positive correlation between past use of QRPs and OSPs, raises the possibility that some criminologists have decided to make good by abandoning QRPs for OSPs. Perhaps their regrets about using QRPs in the past, along with their awareness of the adverse effects of what they did (false positives) and the incentives (e.g., publication) that pushed them to do it, convinced them that OSPs are important for the discipline.

The unclear relationship between QRP and OSP use highlights the need for additional research and theory on the drivers of QRP and OSP use. Across multiple fields, using both direct (e.g., surveys) and indirect methods (e.g., *p*-curve analysis), we are learning much about research behaviors and perceptions of them. Given criminologists’ experience in studying deviance, they are particularly well-suited to contribute to this literature by advancing knowledge on *why* researchers use QRPs and how they may be curbed. In other words, if OSPs are not effective deterrents, how might we otherwise prevent QRPs and promote fuller reporting? Criminological work on the role of morality and social norms in prohibiting deviant behavior may be useful here (Brauer and Tittle 2017; Silver and Silver 2020). In our study, for example, support for QRPs was strongly associated with use of them, as was the perception of others’ use of QRPs (Table 5). Similarly, in the case of OSPs, one meta-scientific study across fields found what the authors referred to as “normative dissonance”: respondents endorsed open science but found that their own behavior and that of their colleagues fell short (Anderson et al. 2007). Our results generally reflect that pattern with respondents seeming to support OSP use to a greater extent than they are currently being used in the field. Here, our data and findings may be a starting point for future projects driven by criminological theories of morality, deviance, and prosocial behavior.

Contrary to our preregistered hypothesis, we did not find a relationship between methodological training and QRP or OSP use. It is somewhat disappointing that methodological training does not predict better research behavior. It could be that our sample is highly-trained—half of respondents had taken six or more methods courses—dampening any associations (Table 2). Of course, that would also mean that highly-trained criminologists still use QRPs at high rates. One reason that methodological training may not be related to QRP use is that QRP use may not reflect ignorance—QRP users may be fully aware of what they are doing. Alternatively, this lack of association could reflect historic norms in methodological training (recall that the plurality of our sample reported being at the senior career stage). Traditionally, methodological training in criminology likely did not emphasize the dangers of QRPs, but more recent training may do so, thus in the future a negative correlation between methodological training and QRP use may emerge. In any event, and as we discuss further in the conclusion, the open science movement elsewhere in social science has emphasized training in transparent methods (e.g., see the Berkeley Initiative for Transparency in the Social Sciences, or BITSS). New training initiatives in criminology should consider following suit.

Turning to career stage, which we did not preregister as a variable of interest, we found that career state was positively correlated with QRP support and negatively correlated with OSP support. More senior researchers were more supportive of using QRPs, and less supportive of using OSPs. Although we did not preregister any hypotheses about these relationships, we will speculate on one possible explanation: they might be a result of more junior researchers learning research practices in an era of greater awareness of the replication crisis and of the dangers of QRP use. Note, however, that previous studies have not found a relationship between career stage and QRP support in other disciplines (Agnoli

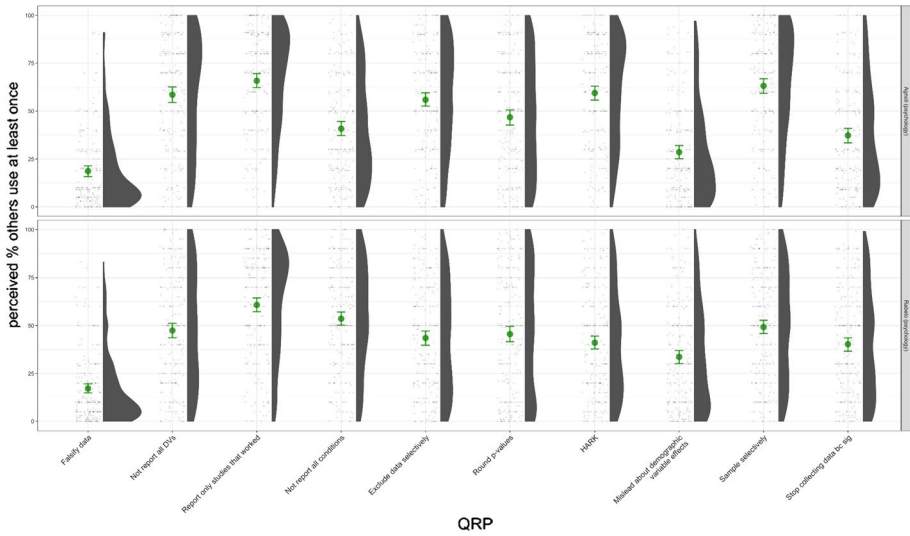


Fig. 5 Perceived Prevalence of QRPs in the Two Published Studies that used Questions most Similar to John et al. (2012). *Notes:* Distribution of perceived % of other Italian (Agnoli et al., 2017) and Brazilian (Rabelo et al., 2020) psychologists using the QRP at least once. 95% confidence intervals calculated using the percentile bootstrapping method (Efron & Tibshirani, 1994)

et al. 2017, p. 9; Makel et al. 2021; Rabelo et al. 2020, p. 680). Set against that background and the fact that we did not preregister relevant hypotheses, we would suggest that conclusions about how senior and junior criminologists differ in their support for QRPs and OSPs await future replications.

Finally, recall that we found that participants' estimates of others' QRP use were quite uniformly distributed from 0 to 100% for multiple practices (Fig. 1). We obtained and re-analyzed the data for published studies that used questions almost identical to those of our study and found a similar pattern of results (<https://osf.io/gcmv7/>). We also obtained data from studies using questions more similar to those in the original John et al. (2012) QRP study in psychology (Fig. 5). Both show a visibly uniform distribution for the perceived prevalence of some practices, like we found in our study. For HARKing, for example, four of the six datasets show distributions that are close to uniform. The two exceptions (Agnoli et al. 2017; Rabelo et al. 2020) are still extremely dispersed, such that the mean is not representative.

These response patterns suggest that in psychology and education research as well as in criminology, researchers do not have much knowledge about the prevalence of QRPs used by their colleagues. One implication is that there may be, at best, weak descriptive norms (i.e., norms based on what behavior is actually common) governing research ethics in these fields. This is important because descriptive norms impact behavior, independent of injunctive norms. Criminologists have also shown that people misperceive their peers' deviant behavior, and that personal offending and self-control shapes such perceptions (Young et al. 2011). Additionally, criminological research on peer effects has also shown that the fear of reputation loss has more effect on behavior than status gains (Thomas and Nguyen 2020). Along these lines, future research is

needed that explores the nature and correlates of scientists' perceptions of their disciplinary colleagues' research behavior as well as their perceptions of the reputational impacts of using QRPs and OSPs. The finding that scholars are unaware of others' research behavior also supports the benefit of studies like ours, which make public and explicit the research practices actually being used in their field.

Limitations

While our study benefited from a large sample size (especially in relation to previous survey studies, <https://osf.io/kj3bfb/>), confidence in our results should be qualified by the low response rate. The low response rate increases the possibility that our sample is biased and thus non-representative of quantitative criminologists. However, the nonresponse rate is not always related to nonresponse bias (Krosnick et al. 2015, p. 6), and in our study any bias would likely be towards underestimating the use of QRPs and overestimating the use of OSPs. This is because it was clear from survey items (although not the recruitment material) that they pertained to QRPs (which are increasingly proscribed) and OSPs (which are increasingly endorsed). We expect that researchers would be both more motivated to participate if they were the type to be concerned about QRPs (Dahlgaard et al. 2019), and that respondents would be inclined to portray their practices along those lines as well. As a result, future research is thus needed that replicates our study with a high-response rate survey.

Our sample was also skewed towards mid-career and senior researchers. This is probably because graduate students and early-career researchers are less likely to be named as the corresponding author in published articles, which is how we sampled criminologists' email addresses. This emphasis on mid-career and senior researchers makes it possible we were surveying researchers who used QRPs earlier in their career, but no longer use them. Still, present support for QRPs suggests that use is enduring. Future research is needed that examines QRP and OSP use among early-career researchers.

Finally, as discussed above, future researchers may wish to clarify possible ambiguity in some of the QRP and OSP descriptions. Recall, for instance that some respondents may have been unclear on whether "preregistration" means only formal preregistration or includes discussions among collaborators about the hypothesis. Ambiguity may also have affected responses to the questions about "replication", as well as the questions about imputation and rounding p -values. The p -value question, for example, did not clarify whether rounding was down to $p=0.05$ or to $p<0.05$, although we assume most respondents interpreted it as $p<0.05$.

Conclusion

If more criminologists forgo QRPs and adopt OSPs, they will get less of the findings they want, but the discipline (and society) will get more of what it needs: reproducible science. We found that most quantitative criminologists in our sample have used QRPs, most believe other researchers use QRPs, and many support the use of QRPs in at least some circumstances. We also found that many criminologists use OSPs, and even more—over 95% of those surveyed—support using OSPs in at least some circumstances.

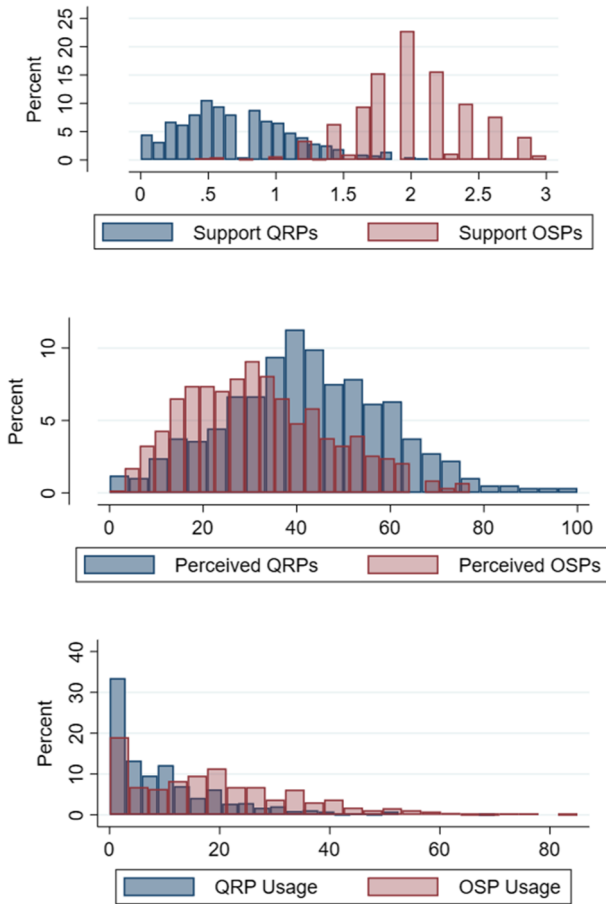
Our findings, then, provide both bad and good news. The bad news is that QRPs appear widespread and are often condoned in criminology. QRPs bias research by exploiting undisclosed flexibility in the data gathering and analysis process to get findings that are desired but often wrong (Beerdse 2021; Simmons et al. 2011). As a field that affects policy (Uggen and Inderbitzin 2010) as well as court decision-making (Chin et al. 2019), QRPs in criminology have real-world consequences. When QRPs are widespread, the evidence used for evidence-based policy is not credible. The good news is that there appears to be an opportunity for improvement, given criminologists' support for OSPs. OSPs make errors detectable (American Association for the Advancement of Science 2019), disincentivize misconduct (Ritchie 2020), and promote public access to science (Ashby 2020).

Behavior is supported, in some part, by beliefs about what others do, which are the foundation of descriptive norms. For some issues, such as undisclosed imputation of data, we found that most criminologists are in agreement that only a small proportion of their colleagues have engaged in the practice. For multiple practices, however, criminologists show little agreement (or knowledge) about the practice's prevalence – indeed, their responses resemble a uniform distribution. In this respect, we hope our results shine some light on criminology research practices and serve as a benchmark for future studies assessing the state of the field. More generally, we hope our work inspires further meta-research. The “flourishing” meta-research in other fields (Munafò et al. 2017, p. 1) has documented the transparency and reproducibility of work in some areas (see Hardwicke et al. 2018). Similar projects would be useful in criminology (e.g., studying whether preregistrations are as common as our sample reported, studying how QRP use has changed over time).

We also hope the room for improvement in the field, which our study documents, will inspire reforms. One factor preventing more widespread OSP use may be of a lack of training. In this respect, the resources developed in cognate fields may be useful (Parsons et al. 2019; Klein et al., 2018a, b). Future training initiatives developed for criminology might highlight the value of preregistration and Registered Reports in addressing the reporting biases that appear to be widespread. Researchers can use free tools to preregister their hypotheses and methods (<https://osf.io/zab38/wiki/home/>), upload data, code, and materials to public repositories (Meyer 2018), and upload preprints (see Ashby 2020).

At the journal and institutional level, several initiatives may assist. For example, journal guidelines (e.g., The Transparency and Openness Guidelines or TOP) have been effective at encouraging authors to make their data open (Hardwicke et al. 2018). Few criminology journals have instituted such guidelines (<https://topfactor.org/>) or adopted the Registered Reports format (<https://www.cos.io/initiatives/registered-reports>). In our view, Registered Reports represent the most promising reform for increasing the credibility of criminological science. As we have discussed, Registered Reports reduce bias by making publication non-contingent on results, disincentivizing (and in many cases prohibiting) QRPs. Finally, in hiring and promotion decisions, criminology departments should take into account paradigms for research assessment that place less weight on results or citation counts, and more on rigor and sharing knowledge through open data and materials (Moher et al. 2020). More generally, these efforts to encourage and reward OSPs and disincentivize QRPs may open the door for researchers to act more in accordance with the norms that we found they already subscribe to.

Appendix: Distribution of Outcomes Used in the Regression Models



NOTES: Distributions of indices used in regression models: support for QRPs and OSPs, perceived prevalence of QRPs and OSPs, and self-use of QRPs and OSPs.

Compliance with ethical standards

Conflict of interest Jason Chin is the president of the Association for Interdisciplinary Meta-research and Open Science(AIMOS), a charitable organization. This is an unpaid position.

References


- Agnoli F, Wicherts JM, Veldkamp CLS, Albiero P, Cubelli R (2017) Questionable research practices among Italian research psychologists. *PLoS ONE* 12(3):e0172792
- Allen C, Mehler DMA (2019) Open science challenges, benefits and tips in early career and beyond. *PLoS Biol* 17(5):e3000246
- American Association for the Advancement of Science (2019) Retraction of the Research Article: Police Violence and the Health of Black Infants
- Anderson MS, Martinson BC, De Vries R (2007) Normative dissonance in science: Results from a national survey of US scientists. *J Empir Res Hum Res Ethics* 2(4):3–14
- Apel R (2013) Sanctions, perceptions, and crime: implications for criminal deterrence. *J Quant Criminol* 29:67–101
- Ashby MPJ (2020) The open-access availability of criminological research to practitioners and policy makers. *J Crim Justice Educ* 32:1–21
- Bakker M, Wicherts JM (2011) The (mis)reporting of statistical results in psychology journals. *Behav Res Methods* 43(3):666–678
- Bakker BN, Jaidka K, Dörr T, Fasching N, Lelkes Y (2020) Questionable and open research practices: attitudes and perceptions among quantitative communication researchers. <https://doi.org/10.31234/osf.io/7uyn5>
- Beerdsen E (2021) Litigation science after the knowledge crisis. *Cornell Law Rev* 106:529–590
- Bem DJ (2011) Feeling the future: experimental evidence for anomalous retroactive influences on cognition and affect. *J Personal Soc Psychol* 100(3):435
- Bishop D (2019) Rein in the four horsemen of irreproducibility. *Nature*, 568(7753)
- Braga AA, Papachristos AV, Hureau DM (2014) The effects of hot spots policing on crime: An updated systematic review and meta-analysis. *Justice Q* 31(4):633–663
- Braga AA, Weisburd D, Turchan B (2018) Focused deterrence strategies and crime control: an updated systematic review and meta-analysis of the empirical evidence. *Criminol Public Policy* 17(1):205–250
- Brauer JR, Tittle CR (2017) When crime is not an option: inspecting the moral filtering of criminal action Alternatives. *Justice Q* 34(5):818–846
- Brodeur A, Cook N, Heyes A (2020) Methods matter: P-hacking and publication bias in causal analysis in economics. *Am Econ Rev* 110(11):3634–3660
- Burt C (2020) Doing better science: improving review & publication protocols to enhance the quality of criminological evidence. *Criminologist* 45(4):1–6
- Cairo AH, Green JD, Forsyth DR, Behler AMC, Raldiris TL (2020) Gray (literature) matters: evidence of selective hypothesis reporting in social psychological research. *Personal Soc Psychol Bull* 46(9):1344–1362
- Camerer CF, Dreber A, Forsell E, Ho T, Huber J, Johannesson M, Kirchler M, Almenberg J, Altmeld A, Chan T, Heikensten E, Holzmeister F, Imai T, Isaksson S, Nave G, Pfeiffer T, Razen M, Wu H (2016) Evaluating replicability of laboratory experiments in economics. *Science* 351(6280):1433–1436
- Camerer CF *et al.* (2018) Evaluating the replicability of social science experiments in *Nature* and *Science* between 2010 and 2015. *Nat Human Behav* 2: 637–644
- Carney, D. My position on “Power Poses”. https://faculty.haas.berkeley.edu/dana_carney/pdf_my%20position%20on%20power%20poses.pdf
- Carpenter J, Kenward M (2012) Multiple imputation and its application. Wiley
- Chin JM (2018) *Abbey* road: the (ongoing) journey to reliable expert evidence. *Can Bar Rev* 96(3):422–459
- Chin JM, Grown B, Mellor DT (2019) Improving expert evidence: the role of open science and transparency. *Ott Law Rev* 50:365–410
- Christensen G, Wang Z, Paluck EL, Swanson N, Birke DJ, Miguel E, Littman R (2019) Open science practices are on the rise: the state of social science (3S) survey. <https://doi.org/10.31222/osf.io/5rksu>
- Dahlgard JO, Hansen JH, Hansen KM, Bhatti Y (2019) Bias in self-reported voting and how it distorts turnout models: disentangling nonresponse bias and overreporting among Danish voters. *Polit Anal* 27(4):590–598
- de Bruin A, Treccani B, Sala SD (2015) Cognitive advantage in bilingualism: an example of publication bias? *Psychol Sci* 26(1):90–107
- DeJong C. St. George S (2018) Measuring journal prestige in criminal justice and criminology. *J Crim Justice Educ* 29(2): 290–309
- Ebersole CR *et al.* (2016) Many Labs 3: evaluating participant pool quality across the academic semester via replication. *J Exp Soc Psychol* 67: 68–82

- Efron B, Tibshirani RJ (1994) An introduction to the bootstrap. CRC Press
- Fanelli D (2012) Negative results are disappearing from most disciplines and countries. *Scientometrics* 90(3):891–904
- Fidler F, Wilcox J (2018) Reproducibility of scientific results. In Zalta EN (ed) *The Stanford Encyclopedia of Philosophy*, Stanford University
- Franco A, Malhotra N, Simonovits G (2014) Publication bias in the social sciences: unlocking the file drawer. *Science* 345(6203):1502–1505
- Franco A, Malhotra N, Simonovits G (2015) Underreporting in political science survey experiments: comparing questionnaires to published results. *Polit Anal* 23:306–312
- Fraser H, Parker T, Nakagawa S, Barnett A, Fiddler F (2018) Questionable research practices in ecology and evolution. *PLoS ONE* 13(7):e0200303
- Gelman A, Loken E (2014) The statistical crisis in science: data-dependent analysis—a “garden of forking paths”—explains why many statistically significant comparisons don’t hold up. *Am Sci* 102(6):460–466
- Gelman A, Skardhamar T, Aaltonen M (2020) Type M error might explain Weisburd’s paradox. *J Quant Criminol* 36(2):395–604
- Hardwicke TE, Mathur MB, MacDonald K, Nilsonne G, Banks GC, Kidwell MC, Mohr AH, Clayton E, Yoon EJ, Tessler MH, Lenne RL, Altman S, Long B, Frank MC (2018) Data availability, reusability, and analytic reproducibility: evaluating the impact of a mandatory open data policy at the journal *Cognition*. *R Soc Open Sci* 5(8):180448
- Hopp C, Hoover GA (2017) How prevalent is academic misconduct in management research? *J Bus Res* 80:73–81. <https://doi.org/10.1016/j.jbusres.2017.07.003>
- Horbach SP, Halfman W (2020) Journal peer review and editorial evaluation: cautious innovator or sleepy giant? *Minerva* 58(2):139–161
- John LK, Loewenstein G, Prelec D (2012) Measuring the prevalence of questionable research practices with incentives for truth telling. *Psychol Sci* 23(5):524–532
- Keeter S, Hatley N, Kennedy C, Lau A (2017) *What Low Response Rates Mean for Telephone Surveys*. Pew Research Center. Retrieved from: <https://www.pewresearch.org/methods/2017/05/15/what-low-response-rates-mean-for-telephone-surveys/>.
- Kidwell MC, Lazarević LB, Baranski E, Hardwicke TE, Piechowski S, Falkenberg LS, Kennett C, Slowik A, Sonnleitner C, Hess-Holden C, Errington TM, Fiedler S, Nosek BA (2016) Badges to acknowledge open practices: a simple, low-cost, effective method for increasing transparency. *PLoS Biol* 14(5):e1002456
- Klein RA. *et al.* (2014) Investigating variation in replicability. *Soc Psychol* 45(3): 142–152
- Klein O. *et al.* (2018a) A practical guide for transparency in psychological science. *Collabra: Psychol* 4(1) <https://online.ucpress.edu/collabra/article/4/1/20/112998/A-Practical-Guidefor-Transparency-in>
- Klein R. A *et al.* (2018b) Many Labs 2: investigating variation in replicability across samples and settings. *Adv Methods Pract Psychol Sci* 1(4): 443–490
- Krosnick JA, Presser S, Fealing KH, Ruggles S (2015) *The Future of Survey Research: Challenges and Opportunities*. The National Science Foundation Advisory Committee for the Social, Behavioral and Economic Sciences Subcommittee on Advancing SBE Survey Research. Available online at: http://www.nsf.gov/sbe/AC_Materials/The_Future_of_Survey_Research.pdf
- Kvarven A, Strømmland E, Johannesson M (2020) Comparing meta-analyses and preregistered multiple-laboratory replication projects. *Nat Hum Behav* 4:423–434
- Levine T, Asada KJ, Carpenter C (2009) Sample sizes and effect sizes are negatively correlated in meta-analyses: evidence and implications of a public bias against nonsignificant findings. *Commun Monogr* 76(3):286–302
- Makel MC, Hodges J, Cook BG, Plucker J (2021) Both questionable and open research practices are prevalent in education research. *Educ Res* 1–12. <https://journals.sagepub.com/doi/full/10.3102/0013189X211001356>
- Manski C (2004) Measuring expectations. *Econometrica* 72:1329–1376
- McNeeley S, Warner JJ (2015) Replication in criminology: a necessary practice. *Eur J Criminol* 12(5):581–597
- Meyer MN (2018) Practical tips for ethical data sharing. *Adv Methods Pract Psychol Sci* 1(1):131–144
- Moher D *et al.* (2020) The Hong Kong Principles for assessing researchers: Fostering research integrity. *PLoS Biol* 18(7): e3000737
- Munafò MR *et al.* (2017) A manifesto for reproducible science. *Nat Human Behav* 1(1): 1–9
- Nelson MS, Wooditch A, Dario LM (2015) Sample size, effect size, and statistical power: a replication study of Weisburd’s paradox. *J Exp Criminol* 11:141–163
- Nelson LD, Simmons J, Simonsohn U (2018) Psychology’s renaissance. *Annu Rev Psychol* 69:511–534

- Nuijten MB, Hartgerink CH, van Assen MA, Epskamp S, Wicherts JM (2016) The prevalence of statistical reporting errors in psychology (1985–2013). *Behav Res Methods* 48(4):1205–1226
- O’Boyle EH Jr, Banks GC, Gonzalez-Mulé E (2017) The chrysalis effect: how ugly initial results metamorphize into beautiful articles. *J Manag* 43(2):376–399
- Open Science Collaboration (2015) *Estimating the reproducibility of psychological science*. *Science*, 349(6251) 943.
- Parsons S, Azevedo F, FORRT (2019) Introducing a Framework for Open and Reproducible Research Training (FORRT). <https://osf.io/bnh7p/>
- Pickett JT (2020) The stewart retractions: a quantitative and qualitative analysis. *Econ J Watch* 7(1):152
- Pridemore WA, Makel MC, Plucker JA (2018) Replication in criminology and the social sciences. *Annu Rev Criminol* 1:19–38
- Rabelo ALA, Farias JEM, Sarmet MM, Joaquim TCR, Hoersting RC, Victorino L, Modesto JGN, Pilati R (2020) Questionable research practices among Brazilian psychological researchers: results from a replication study and an international comparison. *Int J Psychol* 55(4):674–683
- Ritchie S (2020) *Science fictions: how fraud, bias, negligence, and hype undermine the search for truth*. Metropolitan Books, New York
- Rohrer JM *et al.* (2018) Putting the self in self-correction: findings from the loss-of-confidence project. <https://doi.org/10.31234/osf.io/exmb2>
- Rowhani-Farid A, Barnett AG (2018) Badges for sharing data and code at Biostatistics: an observational study. *F1000Research*, 7
- Scheel AM, Schijven M, Lakens D (2020) An excess of positive results: comparing the standard Psychology literature with Registered Reports. <https://doi.org/10.31234/osf.io/p6e9c>
- Schumann S, van der Vegt I, Gill P, Schuurman B (2019) Towards open and reproducible terrorism studies: current trends and next steps. *Perspect Terror* 13(15):61–73
- Silver JR, Silver E (2020) The nature and role of morality in offending: a moral foundations approach. *J Res Crime Delinq* 56(3):343–380
- Simmons JP, Nelson LD, Simonsohn U (2011) False-positive psychology: undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychol Sci* 22(11):1359–1366
- Simonsohn U, Nelson LD, Simmons JP (2014) P-curve: a key to the file-drawer. *J Exp Psychol Gen* 143(2):534
- Sorenson JR (2009) An assessment of the relative impact of criminal justice and criminology journals. *J Crim Justice* 37(5):505–511
- Spellman BA (2015) A short (personal) future history of revolution 2.0. *Perspect Psychol Sci* 10(6):886–899
- Sweeten G (2020) Standard errors in quantitative criminology: taking stock and looking forward. *J Quant Criminol* 36(2):263–272
- Thomas KJ, Nguyen H (2020) Status gains versus status losses: Loss aversion and deviance. *Justice Quarterly*. Advanced online publication. Retrieved from: <https://www.tandfonline.com/doi/abs/https://doi.org/10.1080/07418825.2020.1856400?journalCode=rjyq20>
- Tourangeau R, Conrad FG, Couper MP (2013) *The science of web surveys*. Oxford University Press, New York
- Uggen C, Inderbitzin M (2010) Public criminologies. *Criminol Public Policy* 9(4):725–749
- van Assen MALM, van Aert RCM, Wicherts JM (2015) Meta-analysis using effect size distributions of only statistically significant studies. *Psychol Methods* 20(3):293–309
- Vazire S (2018) Implications of the credibility revolution for productivity, creativity, and progress. *Perspect Psychol Sci* 13(4):411–417
- Vazire S, Holcombe AO (2020) Where are the self-correcting mechanisms in science?. <https://doi.org/10.31234/osf.io/kgqzt>
- Vazire S, Schiavone SR, Bottesini JG (2020) Credibility beyond replicability: improving the four validities in psychological science. <https://doi.org/10.31234/osf.io/bu4d3>
- Weisburd D, Lum CM, Petrosino A (2001) Does research design affect study outcomes in criminal justice? *Ann Am Acad Pol Soc Sci* 578:50–70
- Welsh B, Peel M, Farrington D, Elffers H, Braga A (2011) Research design influence on study outcomes in crime and justice: a partial replication with public area surveillance. *J Exp Criminol* 7:183–198
- Wolfe SE, Lawson SG (2020) The organizational justice effect among criminal justice employees: a meta-analysis. *Criminology* 58(4):619–644
- Wooditch A, Sloan LB, Wu X, Key A (2020) Outcome reporting bias in randomized experiments on substance abuse disorders. *J Quant Criminol* 36(2):273–293
- Young JTN, Barnes JC, Meldrum RC, Weerman FW (2011) Assessing and explaining misperceptions of peer delinquency. *Criminology* 49(2):599–630

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Authors and Affiliations

Jason M. Chin^{1,2}  · Justin T. Pickett³ · Simine Vazire⁴ · Alex O. Holcombe⁵

¹ School of Law, University of Sydney, Sydney, Australia

² Sydney Institute of Criminology, University of Sydney, Sydney, Australia

³ State University of New York At Albany, Albany, USA

⁴ School of Psychology, University of Melbourne, Melbourne, Australia

⁵ School of Psychology, University of Sydney, Sydney, Australia