

Manuscript details

Manuscript number	SSR_2016_64
Title	Methods for Transparent and Reproducible Social Science Research
Article type	Research Paper
Abstract	<p>The social sciences, particularly economics, political science, and psychology, have all taken their turn in the spotlight recently for failures of reproducibility of prominently published research. This article reviews the problems and discusses recent developments and proposed solutions. The problems of publication bias, specification searches (also called data mining or p-hacking), and failures to replicate published research have been known for decades, but a recent surge of research has documented that the problems are still quite prevalent. This has led to a spate of proposed solutions, including study registration, pre-registration of statistical analysis plans, results-blind reviewing, disclosure checklists, and journal requirements of data and code sharing. New methodological tools to test for publication bias, as well as more established tools such as meta-analysis and multiple hypothesis testing adjustment, have become more widely adopted. Lastly, technological improvements such as version control and dynamic documents have made a reproducible research workflow much simpler.</p>

Keywords	reproducibility, research transparency, publication bias, p-hacking, trial registration, data sharing
Manuscript region of origin	North America
Corresponding Author	Garret Christensen
Corresponding Author's Institution	UC Berkeley
Order of Authors	Garret Christensen
Suggested reviewers	Sean Grant, Etienne LeBel

Submission files included in this PDF

File Type	File Name
Manuscript (without Author Details)	Manual_blind.pdf
Title Page (with Author Details)	Manual-coverpage-unblind.pdf
Cover Letter	Copy-of-CoverLetter SSR.docx

To view all the submission files, including those not included in the PDF, click on the manuscript title on your EVISE Homepage, then click 'Download zip file'.

Methods for Transparent and Reproducible Social Science Research

REVIEW BLIND

February 5, 2016

Abstract

The social sciences, particularly economics, political science, and psychology, have all taken their turn in the spotlight recently for failures of reproducibility of prominently published research. This article reviews the problems and discusses recent developments and proposed solutions. The problems of publication bias, specification searches (also called data mining or p-hacking), and failures to replicate published research have been known for decades, but a recent surge of research has documented that the problems are still quite prevalent. This has led to a spate of proposed solutions, including study registration, pre-registration of statistical analysis plans, results-blind reviewing, disclosure checklists, and journal requirements of data and code sharing. New methodological tools to test for publication bias, as well as more established tools such as meta-analysis and multiple hypothesis testing adjustment, have become more widely adopted. Lastly, technological improvements such as version control and dynamic documents have made a reproducible research workflow much simpler.

1 Introduction

Scientific claims should be subject to scrutiny by other researchers and the public at large [Merton, 1973]. An important requirement for such scrutiny is that researchers make their claims transparent in a way that other researchers are able to use easily available resources to form a complete understanding of the methods that were used by the original. In the social sciences, especially given the personal computing and Internet revolutions and the wide availability of data and processing power, it is essential that data, code, and analyses be transparent [Marwick, 2015].

This review article is intended to be a source for empirical social science researchers who desire to make their own research transparent to, and reproducible by, others. The entire process of research, from hypothesis generation to publication, is covered. Although norms differ across disciplines, I attempt to bring a broad view of the empirical social sciences to these recommendations, and hope that students and researchers in any social science field may tailor these recommendations to best fit their field.

The article is laid out as follows: in section 2 I first discuss the motivation for this document: the desire to do ethical research. A major component of ethical social science research is treating research subjects appropriately. This is mandated by federal law and overseen by Institutional Review Boards (IRBs), and should be taken seriously by researchers. But just as treating subjects fairly is ethical, transparent, reproducible research is also a major part of ethical research.

In section 3 I briefly discuss study design, including how to power studies appropriately, including a few practical suggestions on how researchers can work collaboratively to obtain

adequate sample size.

In section 4 I discuss one of the major problems in non-transparent research, specifically publication bias. I also discuss how this problem can be resolved through the practice of registration. Publication bias stems from the fact that published results are overwhelmingly statistically significant. But without knowing how many tests were run (the number of unpublished results), it is impossible to know whether these significant results are meaningful, or whether they are the 5% of tests that we would expect to appear significant due to random sampling, even with no true effect. By publicly registering all studies, we can have a better idea of just how many tests have been run.

In section 5 I discuss researcher degrees of freedom and pre-analysis plans; In addition to registering trials, researchers can also specify their outcomes of interest and their exact methods of analysis to bind their hands during the analysis phase by writing a Pre-Analysis Plan (PAP). This is a relatively new idea in the social sciences, so there is not yet a consensus on when a PAP should be required, what the ideal level of detail is, and how much it should constrain a researcher's hands in the actual analysis, but by pre-specifying analyses, researchers can distinguish between confirmatory and exploratory analysis. I do not necessarily place higher intrinsic value on one or the other, but making the distinction clear is key for appropriate interpretation.

In section 6 I discuss workflow and materials sharing, with an eye on making research replicable by others. Researchers should make their code and data publicly available so that others may repeat and verify their analysis. Making data available incentivizes researchers to make their work accurate in the first place, and makes replication easier for others, improving the scientific process, but also raises the concern of differential privacy, since steps should be

taken to prevent identification of individuals in the data. I also discuss the issue of reporting standards: a standardized list of things that authors should report to help make their work reproducible.

Section 7 concludes and presents a vision for moving forward.

2 Ethical Research

Making one's research transparent and reproducible is a key component of ethical research.

Not engaging in fraud is an obvious component of this.

2.1 Fraud

While most of us are likely to presume that we ourselves would not conduct outright fraud, fraud does indeed occur. From making up fake data to creating bogus e-mail addresses so one could do one's own peer review, the Retraction Watch blog documents a distressingly large amount of deliberate fraud in research. Although the blog tends to specialize in the life sciences, and significantly less money is involved in the social sciences than in medical and pharmaceutical research, there is no reason to believe that social science researchers are inherently more benevolent.

A source for information on fraud is part of the US Department of Health and Human Services, the Office of Research Integrity (ORI), which works to promote research integrity and document misconduct, especially when it involves federally funded research. The misconduct case summaries of the ORI, and the stories of Diederik Stapel [Carey, 2011, Bhattacharjee, 2013] Hwang Woo-Suk [Cyranoski, 2014], Marc Hauser [Johnson, 2012] and Michael La-

Cour [Broockman et al., 2015] should be sobering warnings to us all. As another example, Uri Simonsohn used statistical methods alone to detect fraud in the research of a pair of prominent social psychologists [Simonsohn, 2013].

2.2 Unintentional Bias

Perhaps in addition to the obvious need to avoid deliberate fraud and protect our human subjects is the need to avoid subconsciously biasing our own results.

Nosek et al. [2012] summarize some of the evidence on this subject, concluding that there are many circumstances common to academia and the publishing paradigm that cause researchers to frequently use motivated reasoning:

Because we have directional goals for success, we are likely to bring to bear motivated reasoning to justify research decisions in the name of accuracy, when they are actually in service of career advancement (Fanelli, 2010a). Motivated reasoning is particularly influential when the situation is complex, the available information is ambiguous, and legitimate reasons can be generated for multiple courses of action (Bersoff, 1999; Boiney, Kennedy, & Nye, 1997; Kunda, 1990).

Motivated reasoning can occur without intention. We are more likely to be convinced that our hypothesis is true, accepting uncritically when it is confirmed and scrutinizing heavily when it is not (Bastardi, Uhlmann, & Ross, 2011; Ditto & Lopez, 1992; Lord, Ross, & Lepper, 1979; Pyszczynski & Greenberg, 1987; Trope & Bassok, 1982). With flexible analysis options, we are more likely to find the one that produces a more publishable pattern of results to be more reasonable and

defensible than others (Simmons et al., 2011; Wagenmakers, Wetzels, Borsboom, & van der Maas, 2011). Once we obtain an unexpected result, we are likely to reconstruct our histories and perceive the outcome as something that we could have, even did, anticipate all along—converting a discovery into a confirmatory result (Fischhoff, 1977; Fischhoff & Beyth, 1975). And even if we resist those reasoning biases in the moment, after a few months, we might simply forget the details, whether we had hypothesized the moderator, had good justification for one set of exclusion criteria compared with another, and had really thought that the one dependent variable that showed a significant effect was the key outcome. Instead, we might remember the gist of what the study was and what we found (Reyna & Brainerd, 1995). Forgetting the details provides an opportunity for reimagining the study purpose and results to recall and understand them in their best (i.e., most publishable) light. The reader may, as we do, recall personal examples of such motivated decisions—they are entirely ordinary products of human cognition.

2.3 Institutional Review Boards

In addition to fraud and motivated reasoning, a major ethical concern relates to our human subjects.

2.3.1 History

World history is rife with examples of atrocities conducted in the name of research. Some of these have resulted in major changes in regulations related to research.

Nuremberg Nazi German doctors conducted horrible experiments on subjects during World War II. The “Doctor’s Trial” (USA v. Karl Brandt, et al.) tried 23 defendants, and the verdict included ten principles regarding voluntary consent, societal benefits from the research, minimizing risk, etc., which although never entered as formal regulations in either Germany or the USA, became widely accepted.

Tuskegee and US codification In 1972 whistleblower Peter Buxton revealed to the Associated Press that the US Public Health Service was conducting a 40-year experiment on poor Alabama sharecroppers in which it did not treat those who had syphilis for the disease despite the discovery and verification of penicillin as an effective treatment, and prevented sufferers from obtaining treatment elsewhere. As a result, the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research was formed by law in 1974, and released the Belmont Report in 1979. The Belmont Report contains three basic ethical principles, and three applications:

- Ethical Principles
 - Respect for Persons: “Respect for persons incorporates at least two ethical convictions: first, that individuals should be treated as autonomous agents, and second, that persons with diminished autonomy are entitled to protection.”
 - Beneficence: “Two general rules have been formulated as complementary expressions of beneficent actions in this sense: **(1)** do not harm and **(2)** maximize possible benefits and minimize possible harms.”
 - Justice: “An injustice occurs when some benefit to which a person is entitled is denied without good reason or when some burden is imposed unduly. Another way

of conceiving the principle of justice is that equals ought to be treated equally.”

- Applications

- Informed Consent: “Respect for persons requires that subjects, to the degree that they are capable, be given the opportunity to choose what shall or shall not happen to them. This opportunity is provided when adequate standards for informed consent are satisfied.”
- Assessment of Risks and Benefits: “It is commonly said that benefits and risks must be ‘balanced’ and shown to be ‘in a favorable ratio.’ The metaphorical character of these terms draws attention to the difficulty of making precise judgments. Only on rare occasions will quantitative techniques be available for the scrutiny of research protocols. However, the idea of systematic, nonarbitrary analysis of risks and benefits should be emulated insofar as possible.”
- Selection of Subjects: “Individual justice in the selection of subjects would require that researchers exhibit fairness: thus, they should not offer potentially beneficial research only to some patients who are in their favor or select only ‘undesirable’ persons for risky research. Social justice requires that distinction be drawn between classes of subjects that ought, and ought not, to participate in any particular kind of research, based on the ability of members of that class to bear burdens and on the appropriateness of placing further burdens on already burdened persons.”

In 1981 the Department of Health and Human Services and the Food and Drug Administration adopted regulations in line with the Belmont report, and 15 federal agencies adopted these regulations (45 CFR part 46) as the “Common Rule” in 1991.

In practice, this means that researchers who receive funding from the US government, or who work at institutions that receive federal funding should have their research approved by an Institutional Review Board (IRB). IRB are a decentralized approval body set up by each research organization itself, consisting of at least five members, a mix of men and women, scientists and non-scientists, and at least one member not affiliated with the institution. Since IRBs and the approval process are decentralized, the exact process varies from institution to institution, but one example can be seen at <http://cphs.berkeley.edu>.

When conducting research internationally, researchers should give their human subjects the same protections as those inside the US. Laws in developing countries may not be as well-defined or enforced, but researchers should still register with their US institution's IRB, and obtain approval from the host country government. A list of laws and regulations that cover research in 107 foreign countries is available from the Office for Human Research Protections.

Another key resource for researchers and research conducted outside the US is the Declaration of Helsinki by the World Medical Association (WMA). Originally adopted by the WMA in 1964, the document has significantly influenced the laws and regulations adopted to govern research worldwide.

Lest one think that ethical concerns are limited to monsters of bygone eras, I refer readers to a dilemma caused by a Montana state election experiment by researchers from Stanford and Dartmouth in 2014, who sent 100,000 people official-looking election flyers bearing the state seal weeks before the election.

2.3.2 Training

A large number of universities participate in the Collaborative Institutional Training Initiative at the University of Miami (CITI). Completing their course on Human Subjects Research is often a requirement of being included on a research proposal. For anyone at an institution not affiliated with CITI, the NIH maintains an online training course that is free and open to the public.

3 Study Design

Many issues involving study design are related to transparent and reproducible research. For randomized trials, I refer readers to two excellent resources, Duflo et al. [2007] and Glennerster and Takavarasha [2013], which cover many aspects of how to design and implement a field trial. For studies that are not necessarily randomized trials, I recommend Gertler et al. [2011], or Angrist and Pischke [2008] for those with more statistics training. Here I briefly discuss one aspect of study design especially relevant for reproducible research: determining sample size through power calculations.

3.1 Power Analysis

Given that researchers are working within a null hypothesis testing framework, the power of a study, the probability of rejecting the null hypothesis when it is false, is extremely important. Though 80% power is held as a lower bound for acceptable power in many disciplines such as medical research, the actual power of studies can be much lower. For example, research by Button et al. [2013] found that the median power in neuroscience was 21%. This means

that if a study investigating a true effect were run 100 times, 79 studies would fail to reach significance, meaning that the chance of a false negative is extremely high.

Though false negatives are perhaps the most often discussed issue with low powered studies, they are not the only issue. A second issue is that low powered studies actually decrease the likelihood of a true positive [Button et al., 2013]. This means that when a low powered study does find an effect, the lower the likelihood that this effect is true in the population; it is relatively more likely that it is a false positive. A third issue with low powered studies relates to effect sizes. Small, low powered studies that reach statistical significance will over-estimate the true effect size in the population [Button et al., 2013]. These inflated effect size estimates will make it difficult for others to properly power future studies, and the inaccuracy of the estimate may also be problematic for making decisions based on scientific results.

An obvious way to help mitigate the problems of underpowered studies is to run studies with higher power. However, this process is not always that straightforward. As previously mentioned, effect sizes from published studies are often inflated, and so may not provide the most accurate estimate. Meta-analyses can provide better information, but they also often suffer from publication bias and thus inflated effect sizes. Additionally, effect sizes may be highly heterogeneous between studies, even studies with the same materials and methodologies [Klein et al., 2014]. Thus, using a single point estimate of an effect size from published literature may lead to inaccurate power calculations.

Alternatives to the standard power analysis have been suggested to combat these problems. For example, Perugini et al. [2014] have suggested a technique called ‘safeguard power’ which takes into account the uncertainty surrounding effect size estimates when conducting power analyses. Specifically, they suggest basing power calculations off of the effect size cor-

responding to the lower bound of a 60% confidence interval around the point estimate from published literature. Another approach by McShane and Böckenholt [2014] takes into account the between study variation in effect sizes when conducting power analyses to give a more conservative estimate of the number of participants needed to reach a given level of statistical power. Yet another approach, which is also feasible when an effect size estimate from the previous literature is not available, is to determine the smallest effect size you wish to be able to detect, and power your study to find this effect size [Bloom, 1995].

Additionally, researchers may be able to help one another as well as decrease false-positives by publishing or clearly making available their power calculations. If a reader of a paper saw a clearly stated “this trial was powered to detect an effect size of X,” this would help to put the study into the appropriate statistical context. The parametric assumptions involved (such as the intra-cluster correlation) could also be publicly posted in study protocols to help other researchers learn reasonable assumptions for their own studies.

3.2 Practical Considerations

In many cases, these calculations will reveal the need for a larger sample size than some disciplines are used to handling. There are several ways to mitigate the impact of this.

In psychology, a few of these possible solutions are presented in Collaboration et al. [2014]. Researchers can join crowd-sourced projects where multiple labs share protocols and produce the same experiment, as was done with 13 psychological effects and 36 samples and settings in Klein et al. [2014]. 100 studies were replicated by 270 contributing authors in Open Science Collaboration et al. [2015], with the result that 39% of the originals were considered to have been successfully reproduced. The Collaborative Replications and Education Project (CREP)

tracks findings that can be relatively easily replicated in a teaching setting.

Economists have also discussed how project budgets should play into study design, by maximizing power subject to a budget constraint Duflo et al. [2007]. When data collection is the main cost, the proportion of treatment and control should each be one half, but if treatment is expensive, power can be maximized subject to the project budget using the rule: “the ratio of subjects in the treatment group to those in the comparison should be proportional to the inverse of the square root of their costs.” Another important contribution to this area of power maximization subject to a budget constraint is that power depends on the number of rounds of surveying, and also the autocorrelation of measurements over time. McKenzie [2012] shows that baseline data is of most power when autocorrelation is high, and repeated measurements post-treatment of most power when autocorrelation is low.

4 Registration

One of the problems brought into focus recently is publication bias. Publication bias is the selective publication of only significant results. Thankfully, tools are available for researchers to combat these problems.

4.1 Publication Bias

One of the primary drivers of the recent move towards transparency is increased awareness of publication bias. Numerous papers use collections of published studies to show that the proportion of significant results are extremely unlikely to come from any true population distribution [DeLong and Lang, 1992, Gerber et al., 2001, Ioannidis, 2005]. By examining the

publication rates of null results and significant results from a large set of NSF-funded studies, Franco et al. [2014] show that the selective publication of only significant results may stem from the fact that social science researchers largely fail to write up and submit results from studies resulting in null findings, citing lack of interest or fear of rejection. This idea of rejecting, or not even submitting for review, papers with null-results, is commonly referred to as the “file drawer problem” [Rosenthal, 1979]. In fact, the percentage of null findings published in journals appears to have been decreasing over time, across all disciplines [Fanelli, 2012]. It seems unlikely that this would be an accurate reflection of the state of the universe, unless the hypotheses that scientists are testing are systematically changing over time.

If journals only publish statistically significant results, we have no idea how many of those significant results are evidence of real effects, and which are the 5% of random draws that we should expect to show a significant result with a true population effect of zero. One way to combat this problem is to require registration of all studies undertaken. Ideally we could then search the registry for studies of X on Y. If numerous studies show an effect, we have confidence the effect is real. If 5% of studies show a significant effect, we give these outlier studies less credence.

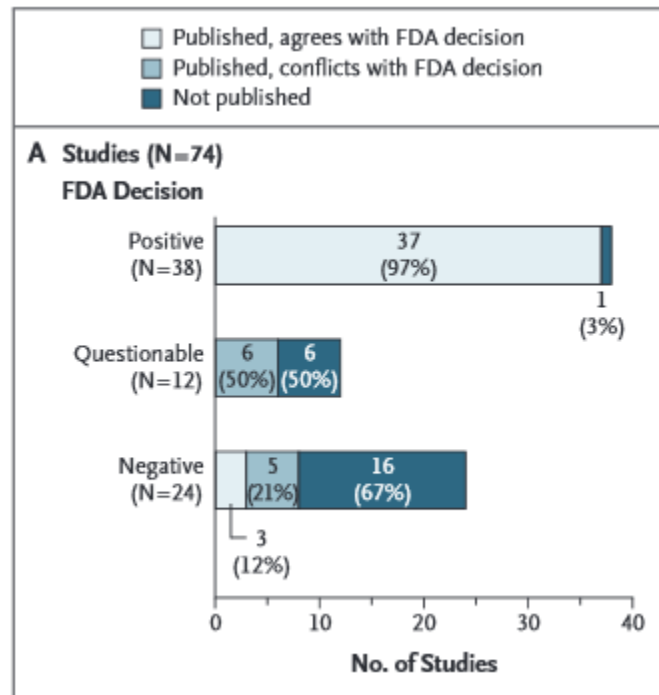
4.2 Trial Registration

A basic definition of registration is to publicly declare *all* research that one plans on conducting. Ideally this is done in a public registry designed to accept registrations in the given research discipline, and ideally the registration takes place before data collection begins.

Registration of randomized trials has achieved wide adoption in medicine, but is still relatively new to the social sciences. After congress passed a law in 1997 requiring the creation

of a registry for FDA-regulated trials, and the NIH created clinicaltrials.gov in 2000, The International Committee of Medical Journal Editors (ICMJE), a collection of editors of top medical journals, instituted a policy of publishing only registered trials in 2005 [De Angelis et al., 2004], and the policy has spread to other journals and been generally accepted by researchers [Laine et al., 2007]. Several other countries have their own national trial registries, and the World Health Organization created the International Clinical Trials Registry Platform (ICTRP) in 2007 to automatically collect all this information in one place.

An example of the benefit of trial registries is detailed in Turner et al. [2008], which details the publication rates of studies related to FDA-approved antidepressants. (See also Ioannidis [2008].) The outcome is unfortunate: essentially all the trials with positive outcomes were published, a 50/50 mix of questionable-outcome studies were published, and a majority of the negative-outcome studies were unpublished a minimum of four years after the study was completed. The figure below shows the drastically different rates of publication, and a large amount of publication bias.



Panel A of Figure 1 reproduced from Turner et al. [2008]

Of course for this sort of exercise to be possible, unless a reader merely assumes that a registered trial without an associated published paper produced a null result (as in Rosenthal [1979]), it requires that the registration site itself obtain outcomes of trials. ClinicalTrials.gov is the only publicly available trial registry that requires such reporting of results, and only for certain FDA trials.¹ Hartung et al. [2014] raises concerns about discrepancies between reporting of outcomes in published papers and in the ClinicalTrials.gov database; as many as 20% of studies had discrepancies in primary outcomes and as many as 33% had discrepancies in reporting of adverse events, so there is definitely room for improvement.

Even with dramatic growth in medical trial registration, problems remain. Not all journals have adopted the ICMJE policy, and complete enforcement is elusive. Mathieu S et al. [2009]

¹Prayle et al. [2012] finds that compliance with results reporting even among those required was fairly low (22%). HHS and NIH took steps in November 2014 to expand the amount of results reporting required. See <http://www.nih.gov/news/health/nov2014/od-19.htm>

looked at trials related to three medical conditions and found that only 46% of studies were registered before the end of the trial with primary outcomes clearly specified. Even among those adequately registered, 31% showed some discrepancies between registered and published outcomes, with bias in favor of statistically significant definitions.

Almost all registration efforts have thus far been limited to randomized control trials, as opposed to observational data. Registering all types of analysis could be accepted, though there are definitely concerns about registering observational work—not least of which is the inability to verify that registration preceded analysis. See Dal-Re et al. [2014] for a recent discussion of the pros and cons.

4.3 Social Science Registries

Registries in the social sciences are newer but are growing ever more popular. A brief overview of the major trial registries is shown in Table 1. The Abdul Latif Jameel Poverty Action Lab began hosting a hypothesis registry in 2009, which was superseded by the American Economic Association’s launch of its own registry for randomized trials in May 2013, which had accumulated over 540 studies in 86 countries by January 2016. The International Initiative for Impact Evaluation (3ie) launched its own registry for evaluations of development programs, the Registry for International Development Impact Evaluations (RIDIE) in September 2013, which had approximately 30 evaluations registered in its first year.

In political science, EGAP: Experiments in Governance and Politics has created a registry as “an unsupervised stopgap function to store designs until the creation of a general registry for social science research. The EGAP registry focuses on designs for experiments and observational studies in governance and politics.” EGAP’s registry had over 260 designs registered

Table 1: Registries in Medicine and the Social Sciences

Registry	Sponsor	Year Started	Study Design	Field	Studies Registered
ClinicalTrials.gov	National Institutes of Health	2000	RCT	Medicine	206,000+
International Clinical Trials Registry Platform	World Health Organization	2007	RCT	Medicine	284,000+
AEA RCT Registry (SocialScienceRegistry.org)	American Economic Association	2013	RCT	Economics	540+
Registry for International Development Impact Evaluations	3ie	2013	Any	Developing country impact evaluation	75+
EGAP Design Registry	Experiments in Governance and Politics	2012	Any	Political Science	260+
Open Science Framework	Center for Open Science	2013	Any	Any	3500+

as of January 2016.²

Another location for registrations is the Open Science Framework (OSF), created by the Center for Open Science. The OSF serves as a broad research management tool that encourages and facilitates transparency (see Nosek et al. [2012].) Registrations are simply unalterable snapshots of research frozen in time, with a persistent URL and timestamp. Researchers can upload their data, code, hypotheses, etc. to the OSF, register it, and then share the resulting URL as proof of registration. OSF registrations can be relatively free-form, but templates exist to conform to standards in different disciplines. Psychology registrations are presently the most numerous on the OSF³

4.4 Meta-Analysis Research

Another method of detecting and dealing with publication bias is to conduct meta-analysis. This method of research collects all published findings on a given topic, analyzes the results collectively, and can detect, and attempt to adjust for, publication bias in the literature. A handful of organizations specialize in producing these systematic reviews, including the Cochrane Collaboration for health studies and the Campbell Collaboration for crime & justice, education, international development, and social welfare research, and the International Initiative for Impact Evaluation (3ie) for social and economic interventions in low- and middle- income countries. The US government supports this type of analysis: the Department of Education's Institute of Education Sciences maintains the What Works Clearinghouse, and the Department of Labor maintains the Clearinghouse for Labor and Evaluation Research (CLEAR), which

²Earlier less-widely adopted attempts to create registries in political science are the Political Science Registered Studies Dataverse (PSRSD, http://spia.uga.edu/faculty_pages/monogan/registration.php) and the PAP Registry of the Experimental Research section of the American Political Science Association (<http://ps-experiments.ucr.edu/browser>).

³See <https://osf.io/explore/activity/#newPublicRegistrations>.

serve to collect and grade the evidentiary value of research on education and labor, respectively. (The synthesis method in the government clearinghouses is not quite as formally statistical in nature as the previously mentioned Collaborations.)

Although quite common in medical research, the tool is not widely used in some parts of the social sciences. But even in economics, where many graduate students are unfamiliar with the technique, important papers exist that have quantitatively synthesized bodies of literature. The unemployment effects of the minimum wage were meta-analyzed in Card and Krueger [1995], and the returns to education in Ashenfelter et al. [1999]. A meta-analysis of 87 meta-analyses in economics shows that publication bias is widespread, but not universal. A helpful resource, the Meta-Analysis of Economics Research Network (MAER-Net) which includes meta-analysis datasets and guidelines for economics researchers interested in conducting a meta-analysis is available [here](#). Also see Stanley [2005], which helpfully describes the tools of meta-analysis, and is part of a special issue of *The Journal of Economic Surveys* dedicated to meta-analysis. Sol Hsiang, lead author of a prominent meta-analysis of 60 studies measuring the effect of climate on human conflict [Hsiang et al., 2013], has also developed the Distributed Meta-Analysis System, an online tool to crowdsource and simplify meta-analysis.

Prominent examples in psychology include meta-analyses of work on the Big 5 Personality Test and job performance [Barrick and Mount, 1991] and predictive validity of the Implicit Association Test [Greenwald et al., 2009]. Simonsohn et al. [2014] also developed a meta-analysis tool that researchers can use to compare the uniform distribution of p-values under the null to the left-skewed distributions observed in research that has been gamed or selectively reported.

5 Researcher Degrees of Freedom

Though registration helps solve the problem of publication bias, it does not solve the problem of fishing for statistical significance within a given study. This problem with research is known as data mining: the manipulation or repeated searching through statistical or regression models unknowingly (or deliberately) until significance is obtained. Simmons et al. [2011] refer to this as “researcher degrees of freedom,” and it has also been referred to as “fishing,” “p-hacking,” or “specification searching” [Humphreys et al., 2013]. The problem has many names because it can take many shapes.

Using flexibility around when to stop collecting data, excluding certain observations, combining and comparing certain conditions, including certain control variables, and combining or transforming certain measures, Simmons et al. [2011] “prove” that listening to the Beatles’ song “When I’m Sixty-Four” made listeners a year and a half younger. The extent and ease of this “fishing” is also described in Humphreys et al. [2013] who use simulations to show that multiplicity of outcome measures, multiplicity of heterogeneous treatment effects (sub-group analyses), and multiplicity of cut-points for turning a continuous outcome variable into a binary outcome, can all be used to virtually guarantee a false positive, even with large sample sizes. They also find that selective adding of covariates can produce false positives with small samples, though they do find little room to produce false positives through arbitrary selection of model for binary outcomes (linear, logit, or probit) regardless of sample size. Gelman and Loken [2013] agree that “[a] dataset can be analyzed in so many different ways (with the choices being not just what statistical test to perform but also decisions on what data to exclude or exclude [sic], what measures to study, what interactions to consider, etc.), that very little in-

formation is provided by the statement that a study came up with a $p < .05$ result.” However, they also conclude that:

the term “fishing” was unfortunate, in that it invokes an image of a researcher trying out comparison after comparison, throwing the line into the lake repeatedly until a fish is snagged. We have no reason to think that researchers regularly do that. We think the real story is that researchers can perform a reasonable analysis given their assumptions and their data, but had the data turned out differently, they could have done other analyses that were just as reasonable in those circumstances. We regret the spread of the terms “fishing” and “p-hacking” (and even “researcher degrees of freedom”) for two reasons: first, because when such terms are used to describe a study, there is the misleading implication that researchers were consciously trying out many different analyses on a single data set; and, second, because it can lead researchers who know they did not try out many different analyses to mistakenly think they are not so strongly subject to problems of researcher degrees of freedom.”

In other words, the problem may be even worse than you think. What can be done to solve it? Part of the answer lies in detailed pre-analysis plans, described below.

5.1 Pre-Analysis Plans

While registration of studies can help to reduce publication bias or the file drawer problem, a pre-analysis plan (PAP), a detailed outline of the analyses that will be conducted in a study, can be used to reduce researcher degrees of freedom. Registration is now the norm in medicine

for randomized trials, and these often include (or link to) prospective statistical analysis plans as part of the project protocol. Official guidance from the US Food and Drug Administration's Center for Drug Evaluation and Research (CDER) from 1998 describes what should be included in a statistical analysis plan and discusses eight items related to data analysis that should be considered: pre-specification of the analysis; analysis sets; missing values and outliers; data transformation; estimation, confidence intervals, and hypothesis testings; adjustment of significance and confidence levels; subgroups, interactions, and covariates; and integrity of data and computer software validity [Food and Drug Administration, 1998]. This is an excellent start, and in the section below I discuss adapting these ideas for a pre-analysis plan in the social sciences.

A PAP contains a specification of the outcomes of the study (sometimes referred to as endpoints in the medical literature), as well as a specification of the methods that will be used to analyze the outcomes. By describing the method(s) of analysis ahead of time, and to some degree tying the hands of the researcher, we reduce the ability to data mine. Though one example of this exists in economics from 2001 [Neumark, 2001], the idea is still quite new to the social sciences. The level of detail varies widely, and the research community is still constructing norms for incorporating these documents into final analyses and papers.

What to Include Suggestions have been made for the detailed contents of these documents. Glennerster and Takavarasha [2013] suggest including the following:

1. the main outcome measures
2. which outcome measures are primary and which are secondary
3. the precise composition of any families that will be used for mean effects analysis

4. the subgroups that will be analyzed
5. the direction of expected impact if we want to use a one-sided test and
6. the primary specification to be used for the analysis

David McKenzie of the World Bank Research Group proposed a list of ten items that should be included in a PAP, reproduced below from the World Bank Development Impact Blog.

1. Description of the sample to be used in the study
2. Key data sources
3. Hypotheses to be tested throughout the causal chain
4. Specify how variables will be constructed
5. Specify the treatment effect equation to be estimated
6. What is the plan for how to deal with multiple outcomes and multiple hypothesis testing?
7. Procedures to be used for addressing survey attrition
8. How will the study deal with outcomes with limited variation?
9. If you are going to be testing a model, include the model
10. Remember to archive it

In their article on researcher degrees of freedom, Simmons, Nelson, and Simonsohn (2011) suggest the following requirements for authors:

1. Authors must decide the rule for terminating data collection before data collection begins and report this rule in the article

2. Authors must collect at least 20 observations per cell or else provide a compelling cost-of-data-collection justification⁴
3. Authors must list all variables collected in a study
4. Authors must report all experimental conditions, including failed manipulations
5. If observations are eliminated, authors must also report what the statistical results are if those observations are included
6. If an analysis includes a covariate, authors must report the statistical results of the analysis without the covariate

Expecting the Unexpected Glennerster and Takavarasha [2013] also mention the “tension between the benefits of the credibility that comes from tying ones hands versus the benefits of flexibility to respond to unforeseen events and results.” Writing a PAP can lend extra credibility to research by making it of a confirmatory nature as opposed to an exploratory nature. Both types of research are absolutely valuable, but knowing the distinction is important. If some sort of restriction on the data, be it a specific functional form, exclusion of outliers, or an interaction term (subgroup analysis) that turns a null effect for the population into a significant effect for some subgroup, is specified ahead of time based on theory or previous research, this can be considered confirmatory research.

Some would say this is of more value than the exploratory research approach of simply running 20 sub-group analyses and finding that one or two are significant. This may be an estimate of a true effect, but should be labeled as exploratory, and future researchers could attempt to confirm this finding by addressing the question of the sub-group specifically. The

⁴It is now widely acknowledged, including by the authors, that this number is too low.

potential downside to pre-stating hypotheses and analysis plans is that no matter how carefully researchers plan ahead, something truly unexpected can occur. (An example discussed at a recent conference was subjects showing up for an experiment stoned. One example from a field experiment involved fatalities from a lightning strike at a school that was part of a competitive girls scholarship program [Kremer et al., 2009].) This is why, even though I may use the phrase “bind our hands,” I suggest that researchers not be punished for conducting research outside the analysis plan. I instead recommend that researchers clearly delineate which analysis was included in the analysis plan, and which was not, so that readers can know what is confirmatory and what is exploratory.

When to Write There is some question as to when one should write one’s pre-analysis plan. “Before you begin to analyze your data” seems like the obvious answer, but this should be precisely defined. One could write the PAP before any baseline survey takes place, after any intervention but before endline, or after endline but before analysis has begun. Glennerster and Takavarasha [2013] and Olken [2015] have an informative discussion of the relative values of PAP timing. If one writes the PAP before the baseline, this is in some sense the purest, most free from accusations of p-hacking, but one could also miss valuable information. For example, suppose in baseline one learns that the intended outcome question is phrased poorly and elicits high rates of non-response, or that there is very little variation in the answers to a survey question. If the PAP was written after baseline, one could have accounted for this, but at the same time, researchers would also be free to change the scope of their analysis—for example, in the baseline survey of a field experiment designed to increase wages revealed that few of the subjects worked outside the home, the researcher could change the focus of the

analysis. This is not necessarily wrong, but it changes the nature of the analysis somewhat.

PAPs could also be written after endline data has been collected but before the investigators have begun to analyze the data. Some have suggested that one could even look at baseline data from the control group only before writing the PAP. This may be problematic, however, since a researcher could learn that the control group had a particularly low or high value of a certain outcome variable, and then choose to include or not include this variable in the analysis as a result. The original research design could have been intended to analyze the increase in secondary school attendance, but looking at the control group, the researcher sees that the control group had a very high rate of attendance, making a significant difference between control and treatment (the treatment effect) unlikely. Learning this after the experiment has concluded and searching for things that might be easily different between treatment and control is more exploratory than confirmatory.

An alternative proposal discussed in Olken [2015] is to remove the treatment status variable from the dataset before looking at the data, which seems to alleviate some of the concerns. However, one could still search for sub-group analyses at this stage. If you parse the outcome data by gender, and males and females have a similar distribution, to find a differential treatment effect by gender would seem unlikely. If male and female had wildly different outcomes, it would seem like a significant interaction is more likely. This is more exploratory than confirmatory.

5.1.1 Examples

Examples of pre-analysis plans in the social sciences are relatively rare, but several examples of published papers resulting from studies with PAP exist. Several of the items below come

from the J-PAL Hypothesis Registry; I highlight those that have publicly available final papers.

- Casey et al. [2012] includes evidence from a large-scale field experiment on community driven development projects in Sierra Leone. The analysis finds no significant benefits. Given the somewhat vague nature of the development projects that resulted from the funding, and the wide variety of potential outcomes, finding significant results would have been relatively easy. In fact, the paper includes an example of how, if they had the latitude to define outcomes without a pre-analysis plan, the authors could have reported either large and significantly positive or negative outcomes, depending on their preferences. The paper also includes a discussion of the history and purpose of pre-analysis plans. The online appendix contains the PAP.
- Oregon expanded its Medicare enrollment through a random lottery in 2008, providing researchers with an ideal avenue to evaluate the benefits of enrollment. Finkelstein et al. [2012], Baicker et al. [2013] and Taubman et al. [2014] show that recipients did not improve in physical health measurements, but were more likely to have insurance, had better self-reported health outcomes, utilized emergency rooms more, and had better detection and management of diabetes. Pre-analysis plans from the project are available at the National Bureau of Economics' site devoted to the project. (See, for example, Taubman et al. [2013], Baicker et al. [2014].)
- The shoe company Toms funded a rigorous evaluation of its in-kind shoe donation program. Researchers wrote a pre-analysis plan before conducting their research, and found no evidence that shoe donations displace local purchasing of shoes. See Wydick et al. [2014], Katz et al. [2013]. The PAP is available in the JPAL Hypothesis Registry. This

is one of many projects that has benefited from a pre-analysis plan because of the involvement of a group with a vested interest, such as a government or corporation. Even researchers skeptical of the need for PAPs in general admit the benefit to publicly pre-stating analysis plans when someone involved has such a clear incentive for results to go a certain direction.

- Researchers from UC San Diego and the World Bank evaluated job training programs run by the Turkish government and found only insignificant improvements and a strongly negative return on investment. See Almeida et al. [2012], Hirshleifer et al. [2014]. The PAP is available in the J-PAL Hypothesis Registry as well as the World Bank Development Impact Blog.
- Teams led by Ben Olken have evaluated multiple randomized interventions in Indonesia. The Generasi program linked community block grants to performance. The PAP are Olken et al. [2009, 2010a] and are available in the J-PAL Hypothesis Registry. The researchers found health improvement, but no education improvement [Olken et al., 2010b, 2014].
- Another project in Indonesia used a field experiment to evaluate different means of poverty targeting for cash transfer programs: proxy-means testing, community-based targeting, and a hybrid of the two. Results show that the proxy-means testing outperformed the other methods by 10%, but that community members were far more satisfied with the community method. The PAP and final paper are available as Olken [2009] and Alatas et al. [2012]
- An example from psychology is a pre-registered replication of an implicit association

test. Existing research showed evidence of stronger racial preferences among fertile women. Hawkins et al. [2015] failed to reproduce this effect in four tries, suggesting the association is weaker than originally found. The resulting manuscript, as well as the time-stamped registration of the analysis plan, can be found on the Open Science Framework at <https://osf.io/g3sca/>.

Additionally, Alejandro Ganimian developed a template for pre-analysis plans that instructors may find useful when teaching transparency methods, or researcher themselves may find useful when developing their own pre-analysis plan.

5.1.2 Observational Pre-Analysis Plans

As with registration, part of the concern with pre-analysis plans is whether the “pre” aspect is verifiable. How can we be sure that a researcher didn’t look at observational data, run a few hypothesis test, and then write the PAP? One way is to use reliably known availability dates of certain datasets such as government administrative data. Verifiable pre-specification of observational research was undertaken in Neumark [2001], which prospectively detailed analysis of the unemployment effects of the minimum wage, a question that has been debated for at least a century [Neumark et al., 2014].⁵

The federal minimum wage changed in October 1996 and September 1997. Neumark submitted a pre-specified research design consisting of the exact estimating equations, variable definitions, and subgroups that would be used to analyze the effect of the minimum wage on unemployment of younger workers using October, November, and December CPS data from

⁵An editorial introduction to Neumark [2001] was accidentally left out of the issue, and published the following month, see Levine [2001]. Others followed Neumark’s paper in spirit by using the same regression specifications on data from Canada [CAMPOLIETI et al., 2006].

1995 through 1998. This detailed plan was submitted to journal editors and reviewers prior to the end of May 1997; the October 1996 data started to become available at the end of May 1997, and Neumark assures readers he had not looked at any published data at the state level prior to submitting his analysis plan.

Neumark's hope was to eliminate the potential for bias due to "author effects." The obvious time stamp of the federal governments release of data indeed makes this possible, but the situation also benefits from the depth and intensity of the debate prior to this study. Neumark had an extensive extant literature to rely on when picking specific functional forms and subgroup analyses to be conducted. He tests two definitions of the minimum wage, the ratio of the minimum wage to the average wage (common in Neumark's previous work), as well as the fraction of workers who benefit from the newly raised minimum wage (used in David Card's earlier work [Card and Krueger, 1992]) and tests both models with and without controls for the employment rate of higher-skilled prime age adults (as recommended by Deere et al. [1995]).

These equations are also each estimated with only a lagged coefficient for minimum wage, and only for the outgoing rotation group (ORG) subset of the data. The equations are estimated for 16-19 year olds, 16-24 year olds, 16-24 year olds with no more than high school education, 20-24 year olds with no more than high school education, and 16-20 and 20-24 year olds (separately) with less than high school education. The results show mostly insignificant results, but that 18 of the 80 specifications result in statistically significant decreases in employment (at the .10 or .05 level), with elasticities ranging from -0.14 to -0.3 for significant estimates and smaller (closer to zero) for insignificant estimates.

How widely could Neumark's method of pre-specification prior to data-release become, and what do we gain from it? Thanks to pre-specification we know exactly how many hy-

pothesis tests Neumark ran (at least 80 coefficients, and more with joint tests), so we know the context in which to appropriately interpret the p-values. This is a significant improvement over much other observational research. Of course, econometricians could still argue about the appropriateness of certain models (whether to include lags or look at contemporaneous effects, for instance) and the analysis suffers from noisy estimates given the relatively small number of changes to state minimum wages compared to other time periods that had been previously analyzed using similar methods.

It is also difficult to see how a researcher could reach this level of detail with a research question with which they were not already intimately familiar; it seems more likely that one would either pre-specify with either a completely inadequate level of detail, or a wildly inappropriate specification. But perhaps this familiarity is a good thing. Much exploratory observational research could continue as is, and for important and thoroughly debated and defined question, confirmatory research could be conducted in a pre-specified fashion. Although pre-specification is difficult, given the vast troves of data released on reliable schedules by governments of developed countries through the world, verifiable pre-specification of observational research could indeed be conducted.

5.1.3 Project Protocols

A project protocol can be somewhat similar to a PAP, but is distinct. A protocol is a detailed recipe or instruction manual for others to use to reproduce an experiment. Protocols are important both in helping solve researcher degrees of freedom problems by making the exact details of analysis known and help avoid selective reporting, as well as in making one's work reproducible. Protocols are standard in the medical literature, as in areas of lab science, but may

be less familiar to those used to working with administrative or observational data. Lab sciences are rife with examples of experiments failing to replicate because of supposedly minor changes such as the brand of bedding in mouse cages, the gender of the laboratory assistant, or the speed at which one stirs a reagent [Sorge et al., 2014, Hines et al., 2014], and the same situation may exist in the social sciences. *Nature* has decided to expand its methods section in order to encourage better reporting.⁶

The social sciences may benefit from more careful documentation of methods. When one uses administrative data this can be accomplished by sharing one's data and code so that analysis is transparent.⁷ This is discussed below in Section 6. With original data collection, researchers should provide very detailed descriptions of what exactly they did. A 33-item checklist of suggested items is contained in the SPIRIT (Standard Protocol Items: Recommendations for Interventional Trials) statement [Chan et al., 2013], including details on the participants, interventions, outcomes, assignment, blinding, data collection, data management, and statistical methods, among other things.

A specific area in which social sciences could improve involves details of randomization. Bruhn and McKenzie [2009] documents the lack of clear explanation pertaining to how randomization was conducted in randomized controlled trials (RCTs) published in economics journals. Variables used for stratification are not described, and the decision of whether to control for baseline characteristics was often done after the fact. While there seems to be internal disagreement in both medicine and the social sciences over the appropriateness of including baseline control variables in regression analysis of a randomized trial, having researchers se-

⁶<http://www.nature.com/news/announcement-reducing-our-irreproducibility-1.12852>

⁷It should be noted that the need for documentation of survey method is not eliminated by using administrative data, the burden simply falls upon the administration.

lectively report whatever method gives them the most significant-seeming results is obviously not the optimal outcome.

The medical literature also exhibits much greater concern over the blinding and concealment of randomized assignment than some of the social science literature. In some situations, blinding is impossible or irrelevant in a social science field experiment: for example, the recipient of a cash transfer needs to know that they received cash in order for the program to have any effect. Also, a social scientist interested in the potential scaling up of a government program may rightfully be unperturbed by some respondents assigned to the control group somehow gaining access to treatment, since this behavior would undoubtedly occur if the program were scaled up and the researcher still has a valid intention to treat estimate. This is not always the case, especially if one wants an accurate estimate of the efficacy of a program or a treatment on the treated estimate. Tales of trials ruined through carelessness with the original randomization assignment as well as tips on how to avoid the same problem are described in Schulz and Grimes [2002]. In addition to Bruhn and McKenzie [2009], political science has produced guidelines for randomization and related disclosure, available at <http://e-gap.org/resources/guides/randomization/>.

Some medicine and science journals have begun to publish protocols. While the advantages of publishing a protocol related to the development of a new procedure (e.g. “we have developed a new method of isolating mRNA”) is clear, the advantages of publishing protocols for randomized trials under way are perhaps less obvious, but still exist. *BioMed Central* and *BMJ Open*, among others, now publish protocols of trials planned or ongoing, with the hopes that this will reduce publication bias, allow patients to see trials in which they might like to enroll, allow funders and researchers to learn of work underway to avoid duplication,

and to allow readers to compare what research was originally proposed to what was actually completed.⁸ *BMJ Open* suggests, but does not require, that its published protocols include the items in the SPIRIT checklist.

Protocols are not a perfect solution, as even in published (or otherwise public) protocols, studies have found important differences between protocols and published results. 60-71% of outcomes described in protocols went unreported in the paper while 62% had major discrepancies between primary outcomes in the protocols and in the published papers, though there was a relatively even mix of these discrepancies favoring significant or insignificant results [Chan A et al., 2004]. Another study found that appropriate level of statistical detail is often lacking in protocols, and there are often discrepancies between protocols and published results [Saqib et al., 2013]. 31% of published papers had some sort of pre-specified plan for their regression adjustments (i.e. specifying which baseline covariates would be controlled for), but only 53% of the plans matched what was published in the ultimate paper.

5.2 Multiple Hypothesis Testing

Several of the PAP and lists of suggestions above include corrections for multiple hypothesis testing. The idea of correcting for multiple tests is widespread in certain fields, but has yet to take hold in the social sciences. Simply put, the idea is that because we are aware of the fact that test statistics and p-values appear significant purely by chance a certain proportion of the time, we can report different, *better* p-values that control for the fact that we are running multiple tests. There are several ways to do this, a few of which are used and explained in a simple and straightforward manner by Anderson [2008]:

⁸See <http://www.biomedcentral.com/authors/protocols> and <http://bmjopen.bmj.com/site/about/guidelines.xhtml#studyprotocols>.

- Report index tests—instead of reporting the outcomes of numerous tests, standardize outcomes and combine them into a smaller number of indices (e.g. instead of separately reporting whether a long-term health intervention reduced blood pressure, diabetes, obesity, cancer, heart disease, and Alzheimer’s, report the results of a single health index.) Kling et al. [2007] implements an index test from the Moving to Opportunity field experiment, using methods developed in biomedicine by O’Brien [1984].
- Control the Family-Wise Error Rate (FWER)—FWER is the probability that at least one true hypothesis in a group is rejected (a type I error), meaning it is advisable when the damage from incorrectly claiming *any* hypotheses are false is important. There are several ways to do this, with the simplest (but very conservative) method being the Bonferroni correction of simply multiplying every original p-value by the number of tests done. Holm’s sequential method involves ordering p-values by class and multiplying the lower p-values by higher discount factors [Holm, 1979]. An efficient recent method is the free step-down resampling method, developed by Westfall and Young [1993].
- Control the False Discovery Rate (FDR)—In situations where a single type I error is not catastrophic, researchers may be willing to use a less conservative method and trade off some incorrect rejections in exchange for greater power. This is possible by controlling the FDR, or the percentage of rejections that are type I errors. Benjamini and Hochberg [1995] details a simple algorithm to control this rate at a chosen level, and Benjamini et al. [2006] describes a two-step procedure with greater power.

5.3 Subgroup Analysis

One aspect of researcher degrees of freedom related to multiple hypothesis testing that seems to have taken hold widely in the medical literature is the aversion to sub-group analysis (“interactions” to most economists). Given the ability to test for a differential effect by many different groupings, crossed with each outcome variable, sub-groups analysis can almost always find some sort of supposedly significant effect. An oft-repeated story in the medical literature revolves around the publication of a study on aspirin after heart attacks. When the editors suggested including 40 subgroup analyses, the authors relented on the condition they include some of their own. Gemini and Libras had worse outcomes when taking aspirin after heart attacks, despite the large beneficial effects for everyone else. (Described in Schulz and Grimes [2005], with the original finding in ISIS-2 (SECOND INTERNATIONAL STUDY OF INFARCT SURVIVAL) COLLABORATIVE GROUP [1988]) Whether in a randomized trial or not, social scientists could benefit from reporting the number of interactions tested, possibly adjusting for multiple hypotheses, and ideally specifying beforehand the interactions to be tested, with a justification from theory or previous evidence as to why the test is of interest.

5.4 Results-Blind Reviewing

A new development in research transparency which helps to address both publication bias and researcher degrees of freedom is results-blind reviewing. In results-blind reviewing, authors submit a detailed research plan *before* conducting the research. They submit this plan to a journal, and the journal rejects or gives an in-principle acceptance of the not-yet-written article based on the scientific merit of the question being asked and the methods proposed to answer

them, as opposed to whether the results pass an arbitrary threshold of statistical significance. Then the authors conduct the research, and their paper is published as long as they don't deviate too much from what they initially proposed. The editors and reviewers have tied their hands and have no ability to accept only significant results, and the authors have less incentive to game their statistical analysis in order to find something significant.

This new mode of publication, called "Registered Reports," is championed by Chris Chambers, psychologist at Cardiff University, and has been adopted by over a dozen journals. See a full list of journals adopting the procedure at <https://osf.io/8mpji/>. *Social Psychology* ran an issue dedicated to this type of article, with an editorial explaining the concept [Nosek and Lakens, 2014]. *AIMS Neuroscience*, which uses this format, published an editorial answering 25 frequently asked questions pertaining to registered reports [Chambers et al., 2014]. A forthcoming special issue of *Comparative Political Studies* will also publish articles of this type [Findley et al., 2016].

6 Replication and Reproducibility

"Economists treat replication the way teenagers treat chastity - as an ideal to be professed but not to be practised."—Daniel Hamermesh, University of Texas at Austin Economics

"Reproducibility is just collaboration with people you don't know, including yourself next week"—Philip Stark, University of California Berkeley Statistics

Replication, in both practice and principle, is a key part of social science research. I first define what exactly we mean by replication using the taxonomy developed in Hamermesh

[2007] and Hunter [2001]. According to Hamermesh, replication comes in a few different shapes: pure, statistical, and scientific.

- Pure: Using the exact same data and the exact same model to see if the published results are reproduced exactly.
- Scientific: Using a different sample from a different population, and similar, but perhaps not identical model .
- Statistical: Using the same model and underlying population but a different sample.

In Hamermesh’s view, this is less relevant to certain fields, such as economics, where researchers are likely to already use as large a sample as is available.

One might imagine a fourth type that uses the same data but probes the data using additional robustness and sensitivity checks. Others have described replication in terms of a spectrum from full replication (independent collection of data and re-running analysis) to reproducibility, where the same data or code are re-used by other researchers [Peng, 2011], and another taxonomy is proposed in Clemens [2016]. Whatever the terminology used, replication or reproducibility, transparent research requires making data and code available to other researchers so they can try and get the same results.

6.1 Code and Workflow

Reproducing research often involves using the exact code and statistical programming done by the original researcher. To make this possible, code needs to be both (1) easily available and (2) easily interpretable. Thanks to several free and easy to use websites described below, code can easily be made available by researchers without requiring funding or website hosting.

Making code easily interpretable is a somewhat more complicated task, nevertheless, the extra effort spent to make a more manageable code pays off with large dividends.

6.1.1 Publicly Sharing Code

Once analysis is complete (or even before this stage) researchers should share their data and code with the public. GitHub (<http://www.github.com>), The Center for Open Science's Open Science Framework (<http://osf.io>), and Harvard University's Dataverse (<http://thedata.org>) are all free repositories for data and code that include easy to use version control.⁹

Version control is a powerful way to archive versions of files so that old versions are not lost and can be returned to if needed. The most naive way to organize a project would be to just name a file “MyAnalysis.do” and then save over it any time you or your coauthor made changes. This of course would result in a huge loss of information. Most people are probably doing some version of the “date and initials” method. Instead of simply calling one's analysis code “MyAnalysis.do” and repeatedly saving over and losing old versions, when you save a new version, you add the date to the file name: “MyAnalysis.2014.08.13.do”, and if a co-author makes changes on the same day, they add their initials: “MyAnalysis.2014.08.13.GC.do” or they change the date: “MyAnalysis.2014.08.14.do”. This can work on small projects, but it is not the best way to work. Why does the operating system say the file from August 13 was modified in October? What if one analysis script file is called 14 times in 9 different files—did you remember to go through and update all the calls? Gentzkow and Shapiro [2014] provide strong evidence of the inadequacy of dating and initialing : “*Not one piece of commercial soft-*

⁹BitBucket (<http://www.bitbucket.org>) is another web service that one can use for free version control and archiving of public data and code.

ware you have on your PC, your phone, your tablet, your car, or any other modern computing device was written with the “date and initial” method.” [emphasis original]

The solution is version control (also referred to as revision control). Version control is free software (Git and Mercurial are popular and free implementations) that stores all versions of files you create, and can easily compare versions of the files to highlight changes, revert to earlier versions, accept or reject changes proposed by a collaborator, and reconcile conflicting versions when different people make changes to the same file. Version control creates a repository, and stores all versions of your files in the repository¹⁰ Web services such as GitHub offer free hosting of these repositories with easy to use web-based interfaces and GUI software, so that you and your collaborators can all access the same files, but you can easily host the repository on a server of your own.

6.1.2 Managing Workflow

Code is just one aspect of a larger structure referred to as “workflow” in Long [2008], by which is meant the combination of data, code, organization, and documentation: everything from file and variable names to folder organization as well as efficient and readable programming, and data storage and documentation. Stata-users should find Long [2008] useful, while R users can refer to Gandrud [2013] for workflow recommendations both general and specific to their respective programming language¹¹. Suggestions here borrow heavily from their excellent work.

Another valuable, more brief work is Matthew Gentzkow and Jesse Shapiro’s manual on

¹⁰Repositories can take up a significant amount of space, but you can avoid this problem by not storing generated files or binaries (.pdf, .docx, .etc) since every user with access to the repository should be able to recompile and generate files on their own. Version control works best with simple text files.

¹¹Also see Kirchkamp

code and data [Gentzkow and Shapiro, 2014]. They come from the same background as many social scientists—they did not take many programming classes, they are interested in tools only to accomplish their applied research goals. Once their data became massive, and their programming problems became massive with it, they figured they should listen to the fulltime programmers and database managers who had spent years and billions of dollars solving these problems. Their manual adapts many of these solutions to data-based social science research.

I also refer undergraduate instructors and others who may be interested to Richard Ball and Norm Medeiros’ Project TIER (Teaching Integrity in Empirical Research), which is a “protocol for comprehensively documenting all the steps of data management and analysis that go into an empirical research paper.” A specific file organization using the Open Science Framework is taught so that teachers can exactly reproduce the work of every student (and so students can reliably get the same answer every time they conduct their analysis).

Software: The movement by many towards open source software such as R and Python may lead to reproducibility and access gains over time. However, many disciplines have long traditions of using proprietary software such as SAS and STATA, and learning a new programming language may be an undesirable additional task in researchers’ busy lives. That said, there are several general coding rules that all researchers should use when organizing and implementing their analysis, and researchers should strive to make their work usable by as many others as possible.

Writing Code: Perhaps the most important rule is to write code instead of working by hand. By that I mean:

- Do not modify data by hand, such as with a spreadsheet. Which is to say, don’t use

Excel.

- Use neither the command line nor drop-down menus nor point-and-click options in statistical software.
- Instead, do everything with scripts.

The simple reason for this is reproducibility. Modifying data in Excel or any similar spreadsheet program leaves no record of the changes made to the data, nor any explanation of the reasoning or timing behind any changes. Although it may seem easy or quick to do a one-time-only cleaning of data in Excel, or make “minor” changes to get the data into a format readable by a researcher’s preferred statistical software, unless these changes are written down in excruciating detail, this is not reproducible by other researchers. It is better to write a programming script that imports the raw data, does all necessary changes, with comments in the code that explain changes, and saves any intermediate data sets used in analysis. Then, researchers can share their initial raw data and their code, and other researchers can reproduce their work exactly.

Though a fair amount of research has been done using pull down menus in SPSS or Stata, it generally makes research less reproducible. A bare minimum if one insists on going this route is to use the built-in command-logging features of the software. In Stata this involves the ‘cmdlog’ command; in SPSS this involves the paste button to add to a syntax.

The ideal is to make everything, including changes like rounding and formatting, done with scripts. Even downloading of data from websites can be done through a script. For example, in R, the `download.file()` function can be used to save data from a website. (Though of course this opens the possibility to the data file changing. When reproducing results from a given

dataset is more important than the data from a specific source, researchers should download their raw dataset once, and never save over it, instead saving all modified intermediate datasets in a separate location.)

Another important way to prevent unintentional changes to data is to always set the seed for random number generators whenever any random numbers are to be used (`set.seed()` in R, `set seed ()` in Stata). Additionally, information about the exact software version used should be included (include the `'version'` command in Stata, or use the `session.info()` command in R) as well as computer processor and operating system information. The casual programmer may assume that sophisticated software would always produce the exact same answer across multiple versions of software and platforms, but this is not the case. This is also definitely not the case with user-written packages. R users can use the `packageVersion()` command, and can run old versions of packages since they are archived at CRAN. Stata users can use the `view-source` command for any `.ado` they use, but since the Statistical Software Components (SSC) unfortunately does not archive old versions, reproducibility may be lost, so ideally researchers would include the actual code for the version of the user-written `.ado` along with their publicly archived data and code files

Finally, two simple organizing principles to consider are:

1. Consider not saving statistical output, and just saving the code and data that generates it.

Obviously this would be unrealistically time consuming for large projects, but the idea is that you should be able to reproduce all steps of your analysis such that you could in theory take this approach.

2. What would happen if you, or your laptop hard drive, were hit by a bus? How easily would anyone else be able to reproduce your work? Hopefully the probability is non-

zero.

6.2 General Workflow Suggestions:

Some specific workflow organization suggestions that should be valid regardless of code or operating system are listed below. Stata-specific suggestions are included in the appendix.

- Do not use spaces in directory or file names, as it complicates referring to them in certain software.
- Use “naming directories”, i.e. a directory beginning with “-” (so that it will appear first alphabetically) inside each directory to explain the contents of the above directory.
- Add name, date, and describe contents, as well as updates, to all scripting files.
- Keep a daily research log, i.e. a detailed written diary of what research is done on a given day. You’ll be surprised how often this will be useful to answer questions about whether you ran a certain test or not, when you did it, and what you called the file.
- Make sure that your script files are self-contained. That is, don’t write a program that only works if you run a group of other files previously in a specific order and then leave things a certain precarious way. You should be able to run intermediate steps of the workflow without disrupting things downstream.
- You can never comment your code too much.
- Indent your code.
- Once you post or distribute code or data, any and all changes require a new file name.
- Separate your cleaning and analysis files; don’t make any new variables that need saving

(or will be used by multiple analysis files) in an analysis file—it is better to only create the variables once so you know they’re identical when used in different analysis files.

- Never name a file “final” because it won’t be.
- Name binary variables “male” instead of “gender” so that the name is more informative.
- Use a prefix such as x_ or temp_ so you know which files can easily be deleted.
- Never change the contents of a variable unless you give it a new name.
- Every variable should have a label.

In addition to making code available to the public, the code itself should be written in a reader-friendly format, referred to as “Literate Programming,” introduced in Knuth [1984] and Knuth [1992]. The basic idea is that “the time is ripe for significantly better documentation of programs, and that we can best achieve this by considering programs to be *works of literature*... Instead of imagining that our main task is to instruct a *computer* what to do, let us concentrate rather on explaining to *human beings* what we want a computer to do.” [emphasis original] Simply put, code should be written in as simple and easily understood a way as possible, and should be very well commented, so that researchers other than the original author can more easily understand the goal of the code.

One tool to make literate (statistical) programming significantly easier is Knitr (see Xie [2013, 2014]) which is built into R Studio¹². Knitr uses R Markdown (a very simple plain text markup language, described at <http://rmarkdown.rstudio.com/>) in which one writes both code and comments that is automatically spun into an easily read and shareable HTML, PDF, or MS Word document. These can be posted and shared for free at RPubS, an easy to

¹²R Studio is a popular free graphical integrated implementation of R, available at <http://www.rstudio.com>.

use hosting service by Rstudio. For Stata users, dynamic documents are slightly less well developed, but E.F. Haghish is actively developing packages (Markdoc, Weaver, Ketchup, and Synlight) that allow users to write their .do files in such a way that the log files output by Stata are formatted and readable in Markdown, HTML, or \LaTeX .

6.3 Sharing Data

In addition to code, researchers should share their data if at all possible. Many journals do not require sharing of data, but the number that do is increasing. Most recently, a consortium of top medical journal editors has proposed a new data-sharing requirement that, if adopted, could drastically improve data availability in medical research [Taichman et al., 2016].

6.3.1 The JMCB Project and Economics

In the field of economics, few, if any journals required sharing of data before “The Journal of Money, Credit, and Banking Project,” published in *The American Economic Review* in 1986 [Dewald et al., 1986]. *The Journal of Money, Credit, and Banking* started the *JMCB Data Storage and Evaluation Project* with NSF funding in 1982, which requested data and code from authors who published in the journal. With a great deal of research funded by the NSF, it should be noted that the NSF has long had an explicit policy of expecting researchers to share their primary data¹³. Despite this, and despite the explicit policy of the *Journal* during the project, at most only 78% of authors provided data to the authors within six months after multiple requests. (This is admittedly an improvement over the 34% from the control group—

¹³“Investigators are expected to share with other researchers, at no more than incremental cost and within a reasonable time, the primary data, samples, physical collections and other supporting materials created or gathered in the course of work under NSF grants. Grantees are expected to encourage and facilitate such sharing.” See <http://www.nsf.gov/bfa/dias/policy/dmp.jsp>

those who published before the *Journal* policy went into effect—who provided data.) Of the papers that were still under review by the *Journal* at the time of the requests for data, one quarter did not even respond to the request, despite the request coming from the same journal considering their paper. The submitted data was often an unlabeled and undocumented mess. Despite this, the authors attempted to replicate nine papers, and often were completely unable to reproduce published results, despite detailed assistance from the original authors.

Unfortunately, nothing much changed with the publication of this important article. A decade later, in a follow-up piece to the JMCB Project published in the *Federal Reserve Bank of St. Louis Review* [Anderson and Dewald, 1994], the authors note that only two economics journals other than the *Review* itself (*Journal of Applied Econometrics*, *Journal of Business and Economic Statistics*) requested data from authors, and neither requested code. The JMCB itself discontinued the policy of requesting data in 1993, though it resumed requesting data in 1996. The authors repeated their experiment with papers presented at the St. Louis Federal Reserve Bank conference in 1992, and obtained similar response rates as those from the original JMCB Project. The flagship economics journal, the *American Economic Review* (AER), did not start requesting data until 2003. Then after a 2003 article showed that nonlinear maximization methods often produce wildly different estimates across different software packages, that not a single AER article tested their solution with different software, and that fully half of queried authors from a chosen issue of the AER, including a then editor of the journal, failed to comply with the policy of providing data and code, editor Ben Bernanke made the data and code policy mandatory in 2004 [McCullough and Vinod, 2003, Bernanke, 2004].

The current data policy from the *American Economic Review* can be seen here: <https://www.aeaweb.org/aer/data.php>. The AER conducted a self-review and found good, but

incomplete, compliance [Glandon, 2010]; others believe much work remains [Anderson et al., 2008]. In addition to all the journals published by the American Economic Association, several top journals, including *Econometrica*, *The Journal of Applied Econometrics*, *The Journal of Money Credit and Banking*, *the Journal of Political Economy*, *The Review of Economics and Statistics*, and *the Review of Economic Studies*, now explicitly require data and code to be submitted at the time of publication. Sadly, one of the top journals, *The Quarterly Journal of Economics* has no data-sharing requirement.

6.3.2 General Repositories

The previous section on the *JMCB* describes only a few journals in one field of the social sciences. Even if the journal to which you submit your research does not require you to supply them with your code and data, researchers should still share these materials. Though some repositories, particularly Harvard's Dataverse, seem equipped to handle data from practically any researcher (a free 1 TB of storage is standard, with more possible upon request), many repositories specialize. The Registry of Research Data Repositories has described over 900 data repositories to help you find the right data repository for your data. A key advantage to using a trusted repository such as one listed there, in lieu of simply posting the data on your own website or making your Dropbox folder public, is that many of these repositories will take your data in its proprietary (Stata, SAS, SPSS, etc.) form, and make it accessible in other formats. Storing your data in a repository with other similar datasets also makes it easier for others to find your data, instead of requiring that they already know of its existence, as would likely be the case with personal websites. Your own personal website is also more likely to be taken offline, should a researcher change schools or retire.

6.3.3 Differential Privacy

One important caveat to making data widely available is that despite anonymization, in the age of big data, sometimes individual subjects can easily be identified. Heffetz and Ligett [2014] recount deliberate data releases by Yahoo! Inc., the Massachusetts state government, and Netflix, that could easily be used to identify individuals in the data, despite the absence of direct identifiers such as names or social security numbers. The problem is that “de-identification does not guarantee anonymization.” This problem is well known in computer science, but solutions are still being developed and are not widely implemented.

6.4 Reporting Standards

In research, the devil truly is in the details. Whether assessing the validity of a research design or attempting to replicate a study, details of what exactly was done must be recorded and made available to other researchers. The exact details that are relevant will likely differ from field to field, but an increasing number of fields have produced centralized checklists that describe (in excruciating detail) what disclosure is required of published studies. These checklists are not often published with the paper, but can be submitted with the original article so that reviewers can check that it has been completed. With nearly infinite and easy web storage, researchers can easily post these materials on their website even if journal editors insist on cutting their methods sections for space reasons.

6.4.1 Randomized Trials and CONSORT

The most widely adopted reporting standard guideline is the Consolidated Standards of Reporting Trials (CONSORT). Reporting standards evolved parallel to construction of clinical-

trials.gov and registration, and are now nearly universally adopted for randomized trials published in medical journals, required or requested by reviewers during the review process. This is still in its infancy in the social sciences.

The original CONSORT was developed in the mid 1990's [Begg C et al., 1996]. After five years, research showed that reporting of essential details, as required by the checklist, had significantly increased in journals requiring the standard [Moher D et al., 2001]. The statement was revised in 2001, and simultaneously published in three of the top journals [Moher et al., 2001]. The statement was again revised in 2010 [Schulz et al., 2010]. The statement is a 25-item checklist pertaining to the title, abstract, introduction, methods, results, and discussion of the article in question, and seeks to delineate the minimum requirements of disclosure that may not be sufficiently addressed through other measures.

6.5 Social Science Reporting Standards

Though a standard akin to CONSORT has not been formally adopted by social science or behavioral science journals, at least as far as we are aware, there have been attempts to do this: in political science, the Experimental Research Section Standards Committee produced a detailed list of items required for disclosure of experiments [Gerber et al., 2014]. This checklist is available here.¹⁴ In economics, one article has highlighted the fact that there is limited discussion of essential features of randomization (How was randomization stratified, if at all? How were control variables determined?), but no standards have been adopted [Bruhn and McKenzie, 2009]. In psychological and behavioral research, an extension to CONSORT for Social and Psychological Interventions (CONSORT-SPI) has been developed in [Montgomery

¹⁴<http://www.davidhendry.net/research-supplemental/gerberetal2014-reportingstandards/gerberetal2014-reportingstandards&appendix1.pdf>

et al., 2013], but so far has not been widely adopted nor required by journals.

6.6 Observational Reporting Standards

Social science has yet to make a serious push for reporting standards in RCTs, let alone observational work, but the medical/epidemiological literature has created standards in this type of work, though they are not as widely adopted as CONSORT. Perhaps the most well-known is the STROBE Statement (Strengthening the Reporting of Observational Studies in Epidemiology)[Von Elm et al., 2007]. STROBE provides checklists for reporting of cohort, case-control, and cross-sectional studies. These standards have been endorsed by approximately 100 journals in the field.¹⁵

Medicine has in fact come up with too many checklists to describe them all individually. Acknowledging that every field and type of research is different, the Equator Network (Enhancing the Quality of Transparency of Health Research) serves as an umbrella organization that seeks to keep tabs on all the best reporting standards and help researchers find which reporting standard is most relevant for their research. See <http://www.equator-network.org/> for more information.

7 Conclusion

If science progresses by standing on the shoulders of giants, then good science requires research to be conducted in a transparent and reproducible fashion. This may require extra up-front work by researchers compared to the current state of affairs. Before one runs an ex-

¹⁵<http://www.strobe-statement.org/index.php?id=strobe-endorsement>

periment, researchers could write down their hypothesis, carefully explain how they are going to test the hypothesis, perhaps going as far as writing down the very regression analysis specification they plan to run, write a detailed protocol of the exact experimental setting, and then post all of this publicly on the Internet in a public repository. In the long run, however, science will reap a reward greater than these costs. Statistical analysis will result in p-values that can be interpreted as intended, and in an appropriate publication bias context. Replicating the work of other researchers will be easy, because their data and code will be in a public repository, and code could be well documented and understandable, and written to easily recreate the original results, ideally with a single click. Science could potentially move forward at a faster rate.

Acknowledgements

I gratefully acknowledge helpful comments from REVIEW BLIND. Funding for this research was provided by an anonymous donor, who played no role in the writing of the article nor in the decision to publish.

Bibliography

- Vivi Alatas, Abhijit Banerjee, Rema Hanna, Benjamin A Olken, and Julia Tobias. Targeting the poor: Evidence from a field experiment in indonesia. *American Economic Review*, 102(4):1206–1240, June 2012. ISSN 0002-8282. doi: 10.1257/aer.102.4.1206. URL <https://www.aeaweb.org/articles.php?doi=10.1257/aer.102.4.1206&fnd=s>.
- Rita Almeida, Sarojini Hirshleifer, David McKenzie, Cristobal Ridao-Cano, and Ahmed Levent Yener. The impact of vocational training for the unemployed in turkey: Pre-analysis plan. *Poverty Action Lab Hypothesis Registry*, February 2012. URL http://www.povertyactionlab.org/sites/default/files/documents/ISKURIE_AnalysisPlan_v4.pdf.
- Michael L. Anderson. Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association*, 103(484):1481–1495, 2008. doi: 10.1198/016214508000000841. URL <http://dx.doi.org/10.1198/016214508000000841>.
- Richard G. Anderson and William G. Dewald. Replication and scientific standards in applied economics a decade after the journal of money, credit and banking project. *Federal Reserve Bank of St. Louis Review*, (Nov):79–83, 1994. URL http://econpapers.repec.org/article/fipfedlrv/y_3a1994_3ai_3anov_3ap_3a79-83.htm.
- Richard G. Anderson, William H. Greene, B. D. McCullough, and H. D. Vinod. The role of data/code archives in the future of economic research. *Journal of Economic Methodology*, 15(1):99–119, 2008. ISSN 1350-178X. doi: 10.1080/13501780801915574. URL <http://dx.doi.org/10.1080/13501780801915574>.
- Joshua D Angrist and Jörn-Steffen Pischke. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press, 2008.
- Orley Ashenfelter, Colm Harmon, and Hessel Oosterbeek. A review of estimates of the schooling/earnings relationship, with tests for publication bias. *Labour economics*, 6(4):453–470, 1999.
- Katherine Baicker, Sarah L. Taubman, Heidi L. Allen, Mira Bernstein, Jonathan H. Gruber, Joseph P. Newhouse, Eric C. Schneider, Bill J. Wright, Alan M. Zaslavsky, and Amy N. Finkelstein. The oregon experiment effects of medicaid on clinical outcomes. *New England Journal of Medicine*, 368(18):1713–1722, 2013. doi: 10.1056/NEJMsa1212321. URL <http://www.nejm.org/doi/full/10.1056/NEJMsa1212321>. PMID: 23635051.
- Katherine Baicker, Amy Finkelstein, and Sarah Taubman. The oregon health insurance experiment: Evidence from criminal charges data, analysis plan. April 2014. URL http://www.nber.org/oregon/files/oregon_hie_crime_analysis_plan.pdf.
- Murray R Barrick and Michael K Mount. The big five personality dimensions and job performance: a meta-analysis. *Personnel psychology*, 44(1):1–26, 1991.

- Begg C, Cho M, Eastwood S, and et al. Improving the quality of reporting of randomized controlled trials: The consort statement. *JAMA*, 276(8):637–639, August 1996. ISSN 0098-7484. doi: 10.1001/jama.1996.03540080059030. URL <http://dx.doi.org/10.1001/jama.1996.03540080059030>.
- Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 289–300, 1995.
- Yoav Benjamini, Abba M Krieger, and Daniel Yekutieli. Adaptive linear step-up procedures that control the false discovery rate. *Biometrika*, 93(3):491–507, 2006.
- Ben S. Bernanke. Editorial statement. *The American Economic Review*, 94(1):404–404, 2004. ISSN 00028282. URL <http://www.jstor.org/stable/3592790>.
- Yudhijit Bhattacharjee. Diederik stapel audacious academic fraud. *The New York Times*, April 2013. ISSN 0362-4331. URL <http://www.nytimes.com/2013/04/28/magazine/diederik-stapels-audacious-academic-fraud.html>.
- Howard S Bloom. Minimum detectable effects a simple way to report the statistical power of experimental designs. *Evaluation review*, 19(5):547–556, 1995.
- David Broockman, Joshua Kalla, and Peter Aronow. Irregularities in lacour (2014). May 2015. URL http://stanford.edu/~dbroock/broockman_kalla_aronow_lg_irregularities.pdf.
- Miriam Bruhn and David McKenzie. In pursuit of balance: Randomization in practice in development field experiments. *American Economic Journal: Applied Economics*, 1(4): 200–232, October 2009. doi: 10.1257/app.1.4.200.
- Katherine S Button, John PA Ioannidis, Claire Mokrysz, Brian A Nosek, Jonathan Flint, Emma SJ Robinson, and Marcus R Munafò. Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, 14(5):365–376, 2013.
- MICHELE CAMPOLIETI, MORLEY GUNDERSON, and CHRIS RIDDELL. Minimum wage impacts from a prespecified research design: Canada 19811997. *Industrial Relations: A Journal of Economy and Society*, 45(2):195–216, 2006. ISSN 1468-232X. doi: 10.1111/j.1468-232X.2006.00424.x. URL <http://dx.doi.org/10.1111/j.1468-232X.2006.00424.x>.
- David Card and Alan B Krueger. Using regional variation in wages to measure the effects of the federal minimum wage. *Industrial & Labor Relations Review*, 46(1):22–37, October 1992.
- David Card and Alan B Krueger. Time-series minimum-wage studies: a meta-analysis. *The American Economic Review*, pages 238–243, 1995.

- Benedict Carey. Noted dutch psychologist, stapel, accused of research fraud. *The New York Times*, November 2011. ISSN 0362-4331. URL <http://www.nytimes.com/2011/11/03/health/research/noted-dutch-psychologist-stapel-accused-of-research-fraud.html>.
- Katherine Casey, Rachel Glennerster, and Edward Miguel. Reshaping institutions: Evidence on aid impacts using a preanalysis plan*. *The Quarterly Journal of Economics*, 127(4): 1755–1812, November 2012. ISSN 0033-5533, 1531-4650. doi: 10.1093/qje/qje027. URL <http://qje.oxfordjournals.org/content/127/4/1755>.
- Christopher D Chambers, Eva Feredoes, Suresh Daniel Muthukumaraswamy, and Peter Etchells. Instead of” playing the game” it is time to change the rules: Registered reports at aims neuroscience and beyond. *AIMS Neuroscience*, 1(1):4–17, 2014.
- A.-W. Chan, J. M. Tetzlaff, P. C. Gotzsche, D. G. Altman, H. Mann, J. A. Berlin, K. Dickersin, A. Hrobjartsson, K. F. Schulz, W. R. Parulekar, K. Krleza-Jeric, A. Laupacis, and D. Moher. SPIRIT 2013 explanation and elaboration: guidance for protocols of clinical trials. *BMJ*, 346(jan08 15):e7586–e7586, January 2013. ISSN 1756-1833. doi: 10.1136/bmj.e7586. URL <http://www.bmj.com/cgi/doi/10.1136/bmj.e7586>.
- Chan A, Hrbjartsson A, Haahr MT, Gtzsche PC, and Altman DG. Empirical evidence for selective reporting of outcomes in randomized trials: Comparison of protocols to published articles. *JAMA*, 291(20):2457–2465, May 2004. ISSN 0098-7484. doi: 10.1001/jama.291.20.2457. URL <http://dx.doi.org/10.1001/jama.291.20.2457>.
- Michael Clemens. The meaning of failed replications: A review and proposal. *CGD Working Paper 399.*, (399), April 2015. URL <http://www.cgdev.org/sites/default/files/CGD-Working-Paper-399-Clemens-Meaning-Failed-Replications.pdf>.
- Michael Clemens. The meaning of failed replications: A review and proposal. *Journal of Economic Surveys*, 2016.
- Open Science Collaboration et al. *Maximizing the Reproducibility of Your Research*. Wiley, New York, NY, 2014. URL <https://osf.io/nte3j/>.
- David Cyranoski. Cloning comeback. *Nature*, 505(7484):468–471, January 2014. ISSN 0028-0836, 1476-4687. doi: 10.1038/505468a. URL <http://www.nature.com/news/cloning-comeback-1.14504>.
- Rafael Dal-Re, John P. Ioannidis, Michael B. Bracken, Patricia A. Buffler, An-Wen Chan, Eduardo L. Franco, Carlo La Vecchia, and Elisabete Weiderpass. Making prospective registration of observational research a reality. *Science Translational Medicine*, 6(224):224cm1–224cm1, February 2014. ISSN 1946-6234, 1946-6242. doi: 10.1126/scitranslmed.3007513. URL <http://stm.sciencemag.org/content/6/224/224cm1>.
- Catherine De Angelis, Jeffrey M. Drazen, Frank A. Frizelle, Charlotte Haug, John Hoey, Richard Horton, and Sheldon Kotzin. Clinical trial registration: A statement from the international committee of medical journal editors. *New England Journal of Medicine*, 351(12): 1250–1251, 2004. doi:10.1056/NEJMe048225.

- Donald Deere, Kevin M. Murphy, and Finis Welch. 1995. Employment and the 1990-1991 minimum-wage hike. *American Economic Review Papers and Proceedings*, 85(2):232–237, May 1995.
- J. Bradford DeLong and Kevin Lang. Are all economic hypotheses false? *Journal of Political Economy*, 100(6):1257–1272, December 1992. ISSN 0022-3808. URL <http://www.jstor.org/stable/2138833>.
- William G. Dewald, Jerry G. Thursby, and Richard G. Anderson. Replication in empirical economics: The journal of money, credit and banking project. *The American Economic Review*, 76(4):587–603, September 1986. ISSN 0002-8282. URL <http://www.jstor.org/stable/1806061>.
- Esther Duflo, Rachel Glennerster, and Michael Kremer. Using randomization in development economics research: A toolkit. *Handbook of development economics*, 4:3895–3962, 2007.
- Daniele Fanelli. Negative results are disappearing from most disciplines and countries. *Scientometrics*, 90(3):891–904, March 2012. ISSN 0138-9130. doi: 10.1007/s11192-011-0494-7. WOS:000300325800009.
- Michael Findley, Nathan M. Jensen, Edmund J. Malesky, and Thomas B. Pepinsky. Introduction: Special issue on research transparency in the social sciences. *Comparative Political Studies*, 2016.
- Amy Finkelstein, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, and Katherine Baicker. The oregon health insurance experiment: Evidence from the first year*. *The Quarterly Journal of Economics*, 127(3):1057–1106, August 2012. ISSN 0033-5533, 1531-4650. doi: 10.1093/qje/qjs020. URL <http://qje.oxfordjournals.org/content/127/3/1057>.
- Food and Drug Administration. Guidance for industry: E9 statistical principles for clinical trials. *Food and Drug Administration: Rockville, Maryland, USA*, 1998. URL <http://www.fda.gov/downloads/drugs/guidancecomplianceregulatoryinformation/guidances/ucm073137.pdf>.
- Annie Franco, Neil Malhotra, and Gabor Simonovits. Publication bias in the social sciences: Unlocking the file drawer. *Science*, 345(6203):1502–1505, September 2014. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.1255484. URL <http://www.sciencemag.org/content/345/6203/1502>.
- Christopher Gandrud. *Reproducible Research with R and R Studio*. CRC Press, 2013.
- Andrew Gelman and Eric Loken. The garden of forking paths: Why multiple comparisons can be a problem, even when there is no fishing expedition or p-hacking and the research hypothesis was posited ahead of time. November 2013. URL http://www.stat.columbia.edu/~gelman/research/unpublished/p_hacking.pdf.

- Matthew Gentzkow and Jesse Shapiro. Code and data for the social sciences: A practitioner's guide. March 2014. URL <http://faculty.chicagobooth.edu/jesse.shapiro/research/CodeAndData.pdf>.
- Alan Gerber, Kevin Arceneaux, Cheryl Boudreau, Conor Dowling, Sunshine Hillygus, Thomas Palfrey, Daniel R. Biggers, and David J. Hendry. Reporting guidelines for experimental research: A report from the experimental research section standards committee. Technical report, 2014. URL <http://www.davidhendry.net/research-supplemental/gerberetal2014-reportingstandards/gerberetal2014-reportingstandards&appendix1.pdf>.
- Alan S. Gerber, Donald P. Green, and David Nickerson. Testing for publication bias in political science. *Political Analysis*, 9(4):385–392, January 2001. ISSN 1047-1987, 1476-4989. URL <http://pan.oxfordjournals.org/content/9/4/385>.
- Paul Gertler, Sebastian Martinez, Patrick Premand, Laura B. Rawlings, and Christel M. J. Vermeersch. *Impact Evaluation in Practice*. World Bank Publications, 2011. ISBN 9780821385418.
- Philip Glandon. Report on the american economic review data availability compliance project. Technical report, Vanderbilt University, November 2010. URL https://aeaweb.org/aer/2011_Data_Compliance_Report.pdf.
- Rachel Glennerster and Kudzai Takavarasha. *Running Randomized Evaluations: A Practical Guide*. Princeton University Press, November 2013. ISBN 9781400848447.
- Anthony G Greenwald, T Andrew Poehlman, Eric Luis Uhlmann, and Mahzarin R Banaji. Understanding and using the implicit association test: Iii. meta-analysis of predictive validity. *Journal of personality and social psychology*, 97(1):17, 2009.
- Daniel S. Hamermesh. Viewpoint: Replication in economics. *Canadian Journal of Economics/Revue canadienne d'economique*, 40(3):715–733, August 2007. ISSN 1540-5982. doi: 10.1111/j.1365-2966.2007.00428.x. URL <http://onlinelibrary.wiley.com/doi/10.1111/j.1365-2966.2007.00428.x/abstract>.
- Daniel M. Hartung, Deborah A. Zarin, Jeanne-Marie Guise, Marian McDonagh, Robin Paynter, and Mark Helfand. Reporting discrepancies between the ClinicalTrials.gov results database and peer-reviewed PublicationsDiscrepancies between ClinicalTrials.gov and peer-reviewed publications. *Annals of Internal Medicine*, 160(7):477–483, April 2014. ISSN 0003-4819. doi: 10.7326/M13-0480. URL <http://dx.doi.org/10.7326/M13-0480>.
- Carlee Beth Hawkins, Cailey E. Fitzgerald, and Brian A. Nosek. In search of an association between conception risk and prejudice. *Psychological Science*, 26(2):249–252, February 2015. doi: 10.1177/0956797614553121. URL <http://pss.sagepub.com/content/26/2/249>.
- Ori Heffetz and Katrina Ligett. Privacy and data-based research. *Journal of Economic Perspectives*, 28(2):75–98, May 2014. ISSN 0895-3309. doi: 10.1257/jep.28.2.

75. URL <https://www-aeaweb-org.proxy.swarthmore.edu/articles.php?doi=10.1257/jep.28.2.75>.
- William C Hines, Ying Su, Irene Kuhn, Kornelia Polyak, and Mina J Bissell. Sorting out the facts: A devil in the details. *Cell reports*, 6(5):779–781, 2014.
- Sarojini Hirshleifer, David McKenzie, Rita Almeida, and Cristobal Ridao-Cano. The impact of vocational training for the unemployed: Experimental evidence from turkey. *The Economic Journal*, pages n/a–n/a, 2014. ISSN 1468-0297. doi: 10.1111/econj.12211. URL <http://dx.doi.org/10.1111/econj.12211>.
- Sture Holm. A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 6(2):pp. 65–70, 1979. ISSN 03036898. URL <http://www.jstor.org/stable/4615733>.
- Solomon M Hsiang, Marshall Burke, and Edward Miguel. Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367, 2013.
- Macartan Humphreys, Raul Sanchez de la Sierra, and Peter van der Windt. Fishing, commitment, and communication: A proposal for comprehensive nonbinding research registration. *Political Analysis*, 21(1):1–20, January 2013. ISSN 1047-1987, 1476-4989. doi: 10.1093/pan/mps021. URL <http://pan.oxfordjournals.org/content/21/1/1>.
- John Hunter. The desperate need for replications. *Journal of Consumer Research*, 28(1): 149–158, June 2001. ISSN 0093-5301. doi: 10.1086/jcr.2001.28.issue-1. URL <http://www.jstor.org/stable/10.1086/321953>.
- John P. A. Ioannidis. Why most published research findings are false. *PLoS Med*, 2(8):e124, August 2005. doi: 10.1371/journal.pmed.0020124. URL <http://dx.doi.org/10.1371/journal.pmed.0020124>.
- John PA Ioannidis. Effectiveness of antidepressants: an evidence myth constructed from a thousand randomized trials? *Philosophy, Ethics, and Humanities in Medicine*, 3(1):14, May 2008. ISSN 1747-5341. doi: 10.1186/1747-5341-3-14. URL <http://www.peh-med.com/content/3/1/14/abstract>.
- ISIS-2 (SECOND INTERNATIONAL STUDY OF INFARCT SURVIVAL) COLLABORATIVE GROUP. RANDOMISED TRIAL OF INTRAVENOUS STREPTOKINASE, ORAL ASPIRIN, BOTH, OR NEITHER AMONG 17 187 CASES OF SUSPECTED ACUTE MYOCARDIAL INFARCTION: ISIS-2. *The Lancet*, 332(8607):349–360, August 1988. ISSN 0140-6736. doi: 10.1016/S0140-6736(88)92833-4. URL <http://www.sciencedirect.com/science/article/pii/S0140673688928334>.
- Carolyn Y. Johnson. Harvard professor who resigned fabricated, manipulated data, US says - the boston globe. *BostonGlobe.com*, September 2012. URL <https://www.bostonglobe.com/news/science/2012/09/05/harvard-professor-who-resigned-fabricated-manipulated-data-says/6gDVkzPNxv1ZDkh4wVnKhO/story.html>.

- Elizabeth Katz, Brendan Janet, Bruce Wydick, and Felipe Gutierrez. Pre-analysis plan: TOMS shoes impact study. Technical report, February 2013. URL http://www.povertyactionlab.org/sites/default/files/documents/Pre-Analysis%20Plan_Wydick_2-12-13.pdf.
- Oliver Kirchkamp. *Workflow of Statistical Data Analysis*. URL <http://www.kirchkamp.de/oekonometrie/pdf/wf-screen2.pdf>.
- Richard A Klein, Kate A Ratliff, Michelangelo Vianello, Reginald B Adams Jr, Štěpán Bahník, Michael J Bernstein, Konrad Bocian, Mark J Brandt, Beach Brooks, Claudia Chloe Brumbaugh, et al. Investigating variation in replicability. *Social Psychology*, 45(3):142–152, 2014.
- Jeffrey R Kling, Jeffrey B Liebman, and Lawrence F Katz. Experimental analysis of neighborhood effects. *Econometrica*, 75(1):83–119, 2007.
- D. E. Knuth. Literate programming. *The Computer Journal*, 27(2):97–111, January 1984. ISSN 0010-4620, 1460-2067. doi: 10.1093/comjnl/27.2.97. URL <http://comjnl.oxfordjournals.org/content/27/2/97>.
- Donald Ervin Knuth. *Literate Programming*. Center for the Study of Language and Information, January 1992. ISBN 9780937073810.
- Michael Kremer, Edward Miguel, and Rebecca Thornton. Incentives to learn. *The Review of Economics and Statistics*, 91(3):437–456, 2009.
- Christine Laine, Richard Horton, Catherine D. DeAngelis, Jeffrey M. Drazen, Frank A. Frizelle, Fiona Godlee, Charlotte Haug, Paul C. Hbert, Sheldon Kotzin, Ana Marusic, Peush Sahni, Torben V. Schroeder, Harold C. Sox, Martin B. Van Der Weyden, and Freek W.A. Verheugt. Clinical trial registration looking back and moving ahead. *New England Journal of Medicine*, 356(26):2734–2736, June 2007. ISSN 0028-4793. doi: 10.1056/NEJMe078110. URL <http://www.nejm.org/doi/full/10.1056/NEJMe078110>.
- David I. Levine. Editor’s introduction to the unemployment effects of minimum wages: Evidence from a prespecified research design. *Industrial Relations: A Journal of Economy and Society*, 40(2):161–162, 2001. ISSN 1468-232X. doi: 10.1111/0019-8676.00204. URL <http://dx.doi.org/10.1111/0019-8676.00204>.
- J. Scott Long. *The Workflow of Data Analysis Using Stata*. Stata Press, December 2008. ISBN 9781597180474.
- Ben Marwick. How computers broke science and what we can do to fix it. *The Conversation*, November 2015. URL <http://theconversation.com/how-computers-broke-science-and-what-we-can-do-to-fix-it-49938>.
- Mathieu S, Boutron I, Moher D, Altman DG, and Ravaud P. Comparison of registered and published primary outcomes in randomized controlled trials. *JAMA*, 302(9):977–984, September 2009. ISSN 0098-7484. doi: 10.1001/jama.2009.1242. URL <http://dx.doi.org/10.1001/jama.2009.1242>.

- B. D. McCullough and H. D. Vinod. Verifying the solution from a nonlinear solver: A case study. *The American Economic Review*, 93(3):873–892, June 2003. ISSN 0002-8282. URL <http://www.jstor.org/stable/3132121>.
- David McKenzie. Beyond baseline and follow-up: The case for more t in experiments. *Journal of Development Economics*, 99(2):210–221, 2012.
- Blakeley B McShane and Ulf Böckenholt. You cannot step into the same river twice when power analyses are optimistic. *Perspectives on Psychological Science*, 9(6):612–625, 2014.
- Robert K Merton. *The sociology of science: Theoretical and empirical investigations*. University of Chicago press, 1973.
- David Moher, Kenneth F. Schulz, and Douglas G. Altman. The CONSORT statement: revised recommendations for improving the quality of reports of parallel group randomized trials. *BMC Medical Research Methodology*, 1(1):2, April 2001. ISSN 1471-2288. doi: 10.1186/1471-2288-1-2. URL <http://www.biomedcentral.com/1471-2288/1/2/abstract>.
- Moher D, Jones A, Lepage L, and for the CONSORT Group. Use of the consort statement and quality of reports of randomized trials: A comparative before-and-after evaluation. *JAMA*, 285(15):1992–1995, April 2001. ISSN 0098-7484. doi: 10.1001/jama.285.15.1992. URL <http://dx.doi.org/10.1001/jama.285.15.1992>.
- Paul Montgomery, Sean Grant, Sally Hopewell, Geraldine Macdonald, David Moher, Susan Michie, and Evan Mayo-Wilson. Protocol for consort-spi: an extension for social and psychological interventions. *Implement Sci*, 8(1):99, 2013.
- David Neumark. The employment effects of minimum wages: Evidence from a prespecified research design. *Industrial Relations: A Journal of Economy and Society*, 40(1): 121–144, January 2001. ISSN 1468-232X. doi: 10.1111/0019-8676.00199. URL <http://onlinelibrary.wiley.com/doi/10.1111/0019-8676.00199/abstract>.
- David Neumark, JM Ian Salas, and William Wascher. Revisiting the minimum wage employment debate: Throwing out the baby with the bathwater? *Industrial & Labor Relations Review*, 67(3):608–648, 2014.
- Brian A Nosek and Daniël Lakens. Registered reports. *Social Psychology*, 45(3):137–141, 2014.
- Brian A. Nosek, Jeffrey R. Spies, and Matt Motyl. Scientific utopia II. restructuring incentives and practices to promote truth over publishability. *Perspectives on Psychological Science*, 7(6):615–631, November 2012. ISSN 1745-6916, 1745-6924. doi: 10.1177/1745691612459058. URL <http://pps.sagepub.com/content/7/6/615>.
- Peter C O’Brien. Procedures for comparing samples with multiple endpoints. *Biometrics*, pages 1079–1087, 1984.
- Benjamin A. Olken. Targeting analysis protocol. Technical report, March 2009. URL <https://www.povertyactionlab.org/sites/default/files/documents/090318a%20Targeting%20Analysis%20Protocol.pdf>.

- Benjamin A Olken. Promises and perils of pre-analysis plans. *The Journal of Economic Perspectives*, 29(3):61–80, 2015.
- Benjamin A. Olken, Junko Onishi, and Susan Wong. Generasi analysis plan. Technical report, April 2009. URL http://www.povertyactionlab.org/sites/default/files/documents/090408_Generasi_Analysis_Plan_CLEAN.pdf.
- Benjamin A. Olken, Junko Onishi, and Susan Wong. Generasi analysis plan: Wave III. Technical report, January 2010a. URL http://www.povertyactionlab.org/sites/default/files/documents/100122_Generasi_AnalysisPlan_Wave_III_CLEAN.pdf.
- Benjamin A. Olken, Junko Onishi, and Susan Wong. Indonesia’s PNPM generasi program : interim impact evaluation report. Technical Report 59567, The World Bank, January 2010b. URL <http://documents.worldbank.org/curated/en/2010/01/13763479/indonesias-pnpm-generasi-program-interim-impact-evaluation-report>.
- Benjamin A. Olken, Junko Onishi, and Susan Wong. Should aid reward performance? evidence from a field experiment on health and education in indonesia. *American Economic Journal: Applied Economics*, 6(4):1–34, 2014. doi: 10.1257/app.6.4.1. URL <http://www.aeaweb.org/articles.php?doi=10.1257/app.6.4.1>.
- Open Science Collaboration et al. Estimating the reproducibility of psychological science. *Science*, 349(6251):aac4716, 2015.
- Roger D. Peng. Reproducible research in computational. *Science*, 334(6060):1226–1227, December 2011. ISSN 0036-8075, 1095-9203. doi: 10.1126/science.1213847. URL <http://www.sciencemag.org/content/334/6060/1226>.
- Marco Perugini, Marcello Gallucci, and Giulio Costantini. Safeguard power as a protection against imprecise power estimates. *Perspectives on Psychological Science*, 9(3):319–332, 2014.
- Andrew P Prayle, Matthew N Hurley, and Alan R Smyth. Compliance with mandatory reporting of clinical trial results on clinicaltrials.gov: cross sectional study. *BMJ*, 344, 2012. ISSN 0959-8138. doi: 10.1136/bmj.d7373.
- Robert Rosenthal. The file drawer problem and tolerance for null results. *Psychological bulletin*, 86(3):638, 1979.
- N. Saquib, J. Saquib, and J. P. A. Ioannidis. Practices and impact of primary outcome adjustment in randomized controlled trials: meta-epidemiologic study. *BMJ*, 347(jul12 2):f4313–f4313, July 2013. ISSN 1756-1833. doi: 10.1136/bmj.f4313. URL <http://www.bmj.com/content/347/bmj.f4313>.
- Kenneth F Schulz and David A Grimes. Allocation concealment in randomised trials: defending against deciphering. *The Lancet*, 359(9306):614–618, February 2002. ISSN 01406736. doi: 10.1016/S0140-6736(02)07750-4. URL [http://www.thelancet.com/journals/lancet/article/PIIS0140-6736\(02\)07750-4/fulltext](http://www.thelancet.com/journals/lancet/article/PIIS0140-6736(02)07750-4/fulltext).

- Kenneth F Schulz and David A Grimes. Multiplicity in randomised trials II: subgroup and interim analyses. *The Lancet*, 365(9471):1657–1661, May 2005. ISSN 0140-6736. doi: 10.1016/S0140-6736(05)66516-6. URL <http://www.sciencedirect.com/science/article/pii/S0140673605665166>.
- Kenneth F. Schulz, Douglas G. Altman, David Moher, and \$author firstName \$author.lastName. CONSORT 2010 statement: updated guidelines for reporting parallel group randomised trials. *BMC Medicine*, 8(1):18, March 2010. ISSN 1741-7015. doi: 10.1186/1741-7015-8-18. URL <http://www.biomedcentral.com/1741-7015/8/18/abstract>.
- Joseph P. Simmons, Leif D. Nelson, and Uri Simonsohn. False-positive psychology undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, 22(11):1359–1366, November 2011. ISSN 0956-7976, 1467-9280. doi: 10.1177/0956797611417632. URL <http://pss.sagepub.com/content/22/11/1359>.
- Uri Simonsohn. Just post it: the lesson from two cases of fabricated data detected by statistics alone. *Psychological science*, 24(10):1875, 2013.
- Uri Simonsohn, Leif D Nelson, and Joseph P Simmons. P-curve: A key to the file-drawer. *Journal of Experimental Psychology: General*, 143(2):534, 2014.
- Robert E Sorge, Loren J Martin, Kelsey A Isbester, Susana G Sotocinal, Sarah Rosen, Alexander H Tuttle, Jeffrey S Wieskopf, Erinn L Acland, Anastassia Dokova, Basil Kadoura, et al. Olfactory exposure to males, including men, causes stress and related analgesia in rodents. *Nature methods*, 2014.
- Tom D Stanley. Beyond publication bias. *Journal of Economic Surveys*, 19(3):309–345, 2005.
- Darren B. Taichman, Joyce Backus, Christopher Baethge, Howard Bauchner, Peter W. de Leeuw, Jeffrey M. Drazen, John Fletcher, Frank A. Frizelle, Trish Groves, Abraham Haileamlak, Astrid James, Christine Laine, Larry Peiperl, Anja Pinborg, Peush Sahni, and Sinan Wu. Sharing clinical trial data: A proposal from the international committee of medical journal editorssharing clinical trial data. *Annals of Internal Medicine*, 2016. doi: 10.7326/M15-2928. URL <http://dx.doi.org/10.7326/M15-2928>.
- Sarah Taubman, Heidi Allen, Katherine Baicker, Bill Wright, and Amy Finkelstein. THE OREGON HEALTH INSURANCE EXPERIMENT: EVIDENCE FROM EMERGENCY DEPARTMENT DATA analysis plan. March 2013. URL <http://www.nber.org/oregon/files/ED%20Analysis%20Plan.pdf>.
- Sarah L. Taubman, Heidi L. Allen, Bill J. Wright, Katherine Baicker, and Amy N. Finkelstein. Medicaid increases emergency-department use: Evidence from oregon’s health insurance experiment. *Science*, 343(6168):263–268, 2014. doi: 10.1126/science.1246183. URL <http://www.sciencemag.org/content/343/6168/263.abstract>.

- Erick H. Turner, Annette M. Matthews, Eftihia Linardatos, Robert A. Tell, and Robert Rosenthal. Selective publication of antidepressant trials and its influence on apparent efficacy. *New England Journal of Medicine*, 358(3):252–260, January 2008. ISSN 0028-4793. doi: 10.1056/NEJMsa065779. URL <http://www.nejm.org/doi/full/10.1056/NEJMsa065779>.
- Erik Von Elm, Douglas G Altman, Matthias Egger, Stuart J Pocock, Peter C Gøtzsche, Jan P Vandenbroucke, Strobe Initiative, et al. The strengthening the reporting of observational studies in epidemiology (strobe) statement: guidelines for reporting observational studies. *Preventive medicine*, 45(4):247–251, 2007.
- Peter H. Westfall and S. Stanley Young. *Resampling-Based Multiple Testing*. Wiley, 1993.
- Bruce Wydick, Elizabeth Katz, and Brendan Janet. Do in-kind transfers damage local markets? the case of TOMS shoe donations in el salvador. *Journal of Development Effectiveness*, 6(3):249–267, May 2014. ISSN 1943-9342. doi: 10.1080/19439342.2014.919012. URL <http://dx.doi.org/10.1080/19439342.2014.919012>.
- Yihui Xie. *Dynamic Documents with R and knitr*. CRC Press, July 2013. ISBN 9781482203530.
- Yihui Xie. knitr: A comprehensive tool for reproducible research in r. In *Implementing Reproducible Research*, pages 3–32. CRC Press, April 2014. ISBN 9781466561595.

A Glossary of Terms

For researchers unfamiliar with any of the terms involved, I include a glossary of terms.

- Analysis Plan: See pre-analysis plan
- Data citation: The practice of specifically citing datasets, and not just the paper in which a dataset was used. This helps other researchers to find data and rewards researchers who share data, leading to better science. Read more at <http://www.icpsr.umich.edu/icpsrweb/ICPSR/curation/citations.jsp>.
- Data mining: Searching blindly or repeatedly through data to find supposedly statistically significant relationships. While not inherently wrong, if done without a plan or without adjusting for multiple hypothesis testing, test statistics and p-values that result no longer hold their traditional meaning, and can lead to research that cannot be replicated.
- Data sharing: Researchers making the data they use in an analysis available to other researchers, ideally through a trusted public archive.
- Design-based publication: See results-blind review.
- Disclosure: In addition to the widely accepted norm of publicly declaring all potential conflicts of interest, researchers should detail all the ways in which they test a hypothesis (e.g. include the outcome from all regression specifications tested in the appendix.)
- Fishing: See data mining.
- Literate Programming: The idea of writing programming code designed to be read and easily understood by a human. Use of this best practice can make a researchers code far more easily reproducible by others.
- Multiple hypothesis correction: Statistically taking into account the fact that multiple hypotheses have been tested. This tends to decrease the reported statistical significance of any individual test conducted. The oldest method, known as the Bonferroni correction, simply divides the significance threshold by the number of tests. This is quite conservative, and more modern methods are helpfully described in Anderson [2008].
- Open Access: Journals, or articles that are freely available to the public, as opposed to available only to paid subscribers. See [HowOpenIsIt?](#) for a detailed definition of the spectrum of openness.
- Open Data: See data sharing.
- P-hacking: See data mining.
- P-value: The statistic researchers use to make judgments regarding statistical significance, which is quite often misunderstood. It is the probability of obtaining a test statistic at least as extreme as the observed test statistic when the null hypothesis is true.
- Pre-analysis plan: A document that details, ahead of time, the statistical analysis that will be conducted for a given research project. Outcomes, control variables, and regression specifications are all written in as much detail as possible. This serves to make research more confirmatory in nature.

- Pre-specification: Detailing the method of analysis before actually beginning data work; the same as writing a pre-analysis plan.
- Protocol: A general term meaning a document that provides a detailed description of a research project, ideally written before the project takes place, and in enough detail that other researchers may reproduce the project on their own. Often used in the context of human subjects IRB protocols, but increasingly used in connection with pre-analysis plans.
- Publication Bias: The unfortunate fact that research is often only published when it contains the rejection of a null hypothesis test, i.e. a statistically significant relationship. Reviewers or journal editors may consider a null finding to be of less interest, or a researcher may fail to write up a null result, even though the null result may be the truth.
- Registration: Publicly declaring that an investigation of a hypothesis is being or will be undertaken.
 - Study Registration: Registering a research project generally.
 - Trial Registration: Registering a randomized trial.
- Registry: A database of registered studies or trials. For instance, socialscienceregistry.org or clinicaltrials.gov. Some of the largest registries only accept randomized trials, hence the frequent discussion of trial registries.
- Registered Reports: See results-blind review.
- Replicable: See reproducible.
- Replication: The idea of conducting an existing research project over again, with the hope of obtaining the same result. A subtle taxonomy exists, and unfortunately there is disagreement, which is explained in Hamermesh [2007] and Clemens [2015].
 - Pure Replication: Re-running existing code, with error-checking, on the original dataset and seeing if the published results are obtained.
 - Scientific Replication: Attempting to reproduce the published results with a new sample, with the same code or with slight variations from the original analysis.
- Reproducible: The test of whether research can redone by another researcher and produce the same results as the original.
- Researcher Degrees of Freedom: the flexibility that a researcher has in data analysis, whether consciously abused or not. See data mining.
- Results-blind Review: To help reduce publication bias, peer review can take place before results of a study are determined. Reviewers evaluate the design of a study to see whether the question is important and whether the study is well-designed. Good studies are given in-principle acceptance, and cannot be discriminated against for a null result, which, after all, may be the truth. See <https://osf.io/8mpji/wiki/home/> for journals practicing this form of publication.
- Specification searching: Testing numerous regression specifications and reporting only the model that produces the desired results. See data mining.

- **Trusted Digital Repository:** A location for storing data that others can believe will not be manipulated, and will be available into the future. Storing data here is superior to simply posting on an individual website, since it is more easily accessible and less easily changed.
- **Version Control:** A method of tracking every edit made to a computer file. This is often quite useful for empirical researchers who may edit their programming code hundreds or thousands of times.

B Stata-specific Coding Suggestions

- Use the full set of missing values available to you (“a”-“z”, not exclusively “.”) in order to distinguish between “don’t know” and “didn’t ask” or other distinct reasons for missing data.
- Make sure code always produces the same result—if you use anything randomly generated, set the seed. When sorting or merging, you need to be sure to uniquely specify observations, because if you don’t, Stata does something arbitrary and not repeatable. So instead of just sorting or merging on ‘ID’ when there are multiple observations per ID, sort by ‘ID’ and ‘name.’ You can use the ‘duplicates’ command to test whether the *varlist* you use uniquely identifies observations. The ‘sort, stable’ command can be used, though it is slower.
- Use the ‘version’ command in your .do file to ensure that other researchers who run your code with a newer version of Stata get the same results.
- Don’t use abbreviations for variables (which may become unstable after adding variables) or commands (beyond reason).
- Avoid using global macros, and use locals instead. (This is a common piece of programming advice: since globals can be accessed across different functions or spaces, they can create contradictions or inconsistent dependencies. In Stata, it’s possible they can be safely used to define directory paths so collaborators can work across different computers, but that should likely be the extent of their use.)
- Use locals for varlists to ensure that long lists of variables include the same variables whenever intended.
- Use computer-stored versions of numerical output instead of manually typing in numbers or copying and pasting. For example, instead of copying and pasting the mean after a ‘summ’ command, refer to ‘r(mean)’. Use the ‘return list’ command to see a full list of stored values after a regular command and the ‘ereturn list’ after estimation commands.
- If you have a master .do file that calls other .do files, which each have their own .log file, you can run multiple log files at the same time (so you have a master .log file).
- Use the ‘label data’ and ‘notes’ commands to label datasets and help yourself and other researchers easily identify the contents.
- Use the ‘notes’ command for variables as well for identifying information that is too long for the variable label.

- Use the ‘datasignature’ command to generate a hash or checksum and help ensure that data is the same as before.
- In addition to labeling your variables, you should also use value labels for all categorical variables. Include the numerical value in the label, however, since without it, it can be hard to tell what numerical value is actually meant by a given category.
- Even though Stata is case sensitive, don’t use capital letters in variable names since not all software packages are case sensitive.
- Make your files as non-proprietary as possible (use the ‘saveold’ command to enable those with earlier versions to use your data. This is why trusted repositories are so useful—they’ll do this for you.)

Methods for Transparent and Reproducible Social Science Research

Garret Christensen*

February 5, 2016

Abstract

The social sciences, particularly economics, political science, and psychology, have all taken their turn in the spotlight recently for failures of reproducibility of prominently published research. This article reviews the problems and discusses recent developments and proposed solutions. The problems of publication bias, specification searches (also called data mining or p-hacking), and failures to replicate published research have been known for decades, but a recent surge of research has documented that the problems are still quite prevalent. This has led to a spate of proposed solutions, including study registration, pre-registration of statistical analysis plans, results-blind reviewing, disclosure checklists, and journal requirements of data and code sharing. New methodological tools to test for publication bias, as well as

*UC Berkeley, Berkeley Initiative for Transparency in the Social Sciences. Please send correspondence to garret@berkeley.edu, or find the version controlled history of this document on github.

more established tools such as meta-analysis and multiple hypothesis testing adjustment, have become more widely adopted. Lastly, technological improvements such as version control and dynamic documents have made a reproducible research workflow much simpler.

February 5, 2016

Dear Stephanie Moller,

Enclosed is a manuscript to be considered for publication in *Social Science Research*. In the paper I review the recent trend in psychology, political science, economics, and the social sciences more generally, towards transparent and reproducible research. The problems of publication bias, specification searches (also called data mining or p-hacking), and failures to replicate published research have been known for decades, but recent research has documented that the problems are still quite prevalent. This has led to a spate of proposed solutions, including study registration, pre-registration of statistical analysis plans, results-blind reviewing, disclosure checklists, and journal requirements of data and code sharing. New methodological tools to test for publication bias, as well as more established tools such as meta-analysis and multiple hypothesis testing adjustment, have become more widely adopted. Lastly, technological improvements such as version control and dynamic documents have made a reproducible research workflow much simpler.

Funding for this work was provided by an anonymous donor. They played no role in the writing of the article, nor the decision to publish. I declare that there are no conflicts of interest, and that this work has not been published elsewhere and is not currently under consideration elsewhere. Thank you for your consideration. Please feel free to contact me via e-mail at garret@berkeley.edu or by phone at (510)847-6081 if you have any questions.

Sincerely,

Garret Christensen
UC Berkeley, Berkeley Initiative for Transparency in the Social Sciences