

REPRODUCIBILITY IN MANAGEMENT SCIENCE*

MILOŠ FIŠAR, BEN GREINER, CHRISTOPH HUBER, ELENA KATOK, ALI I. OZKES,
AND THE MANAGEMENT SCIENCE REPRODUCIBILITY COLLABORATION†

DECEMBER 6, 2023

ABSTRACT

With the help of more than 700 reviewers we assess the reproducibility of nearly 500 articles published in the journal *Management Science* before and after the introduction of a new Data and Code Disclosure policy in 2019. When considering only articles for which data accessibility and hard- and software requirements were not an obstacle for reviewers, the results of more than 95% of articles under the new disclosure policy could be fully or largely computationally reproduced. However, for 29% of articles at least part of the dataset was not accessible to the reviewer. Considering all articles in our sample reduces the share of reproduced articles to 68%. These figures represent a significant increase compared to the period before the introduction of the disclosure policy, where only 12% of articles voluntarily provided replication materials, out of which 55% could be (largely) reproduced. Substantial heterogeneity in reproducibility rates across different fields is mainly driven by differences in dataset accessibility. Other reasons for unsuccessful reproduction attempts include missing code, unresolvable code errors, weak or missing documentation, but also soft- and hardware requirements and code complexity. Our findings highlight the importance of journal code and data disclosure policies, and suggest potential avenues for enhancing their effectiveness.

Keywords: reproducibility, replication, crowd science

*We thank the members of the Management Science Reproducibility Collaboration for their contributions, Matthew D. Houston and Lucas Unterweger for research support, and Anna Dreber, Susann Fiedler, Lars Vilhuber, two anonymous reviewers, and the Associate and Department editor for helpful comments.

†Fišar: Masaryk University, e-mail: milos.fisar AT econ.muni.cz.

Greiner: Wirtschaftsuniversität Wien, e-mail: bgreiner AT wu.ac.at, and University of New South Wales.

Huber: Wirtschaftsuniversität Wien, e-mail: christoph.huber AT wu.ac.at.

Katok: University of Texas at Dallas, e-mail: ekatok AT utdallas.edu.

Ozkes: SKEMA Business School, Université Côte d’Azur (GREDEG), e-mail: ali.ozkes AT skema.edu, and Université Paris-Dauphine - PSL (LAMSADE).

A complete list of the members of the Management Science Reproducibility Collaboration is included in Appendix A.

I INTRODUCTION

To be relevant and credible, scientific results have to be verifiable. The integrity of academic endeavors rests upon reproducibility, wherein independent researchers obtain consistent results using the same methodology and data, and replicability, which involves the application of similar procedures to new data.

The significance of these twin principles for scientific research is commonly agreed upon. Yet, recent assessments of empirical studies in the social sciences suggest a concerning rate of non-reproducibility or non-replicability (e.g., Ioannidis, 2005; Ioannidis and Doucouliagos, 2013; Open Science Collaboration, 2015). A replicability crisis does not only erode the confidence in individual studies, but casts a shadow over entire fields and literatures, and may potentially compromise business and policy decisions based on these findings. Assessing and addressing these issues is imperative to maintain the credibility of social science research, including management, psychology, economics, sociology, and political science, and its subsequent applications in economic policies and management strategies, guiding societal progress.

Several reasons are cited in the literature as contributing to reduced replicability, such as publication bias (De Long and Lang, 1992), undisclosed analysis flexibility (Simmons et al., 2011), p -hacking (Brodeur et al., 2016), and plain fraud (John et al., 2012; List et al., 2001). Ensuring that published results can be reliably reproduced is a necessary foundation for addressing these issues. While tackling the underlying reasons for limited replicability may be difficult, the ability to reproduce results based on the original data and analyses can be seen as a minimum criterion for scientific credibility to be expected from all published research (Christensen and Miguel, 2018; Nagel, 2018; Welch, 2019). Indeed, if published results cannot be reproduced because data are unavailable, or code used for data or numerical analysis is missing, poorly documented, or error-ridden, then the replicability crisis is partly also a reproducibility crisis.

In this study, we directly assess the reproducibility of results reported in nearly 500 research articles published in *Management Science*, a premier general interest academic journal that comprises of 14 departments covering a broad variety of areas in business and management. In 2019, the journal introduced a new Policy for Data and Code Disclosure,¹ which stipulates that “Authors of accepted papers ... must provide ... the data, programs, and other details of the experiment and computations sufficient to permit replication.” While our focus is primarily on assessing the reproducibility of work published since the disclosure policy went into effect, we also analyze articles accepted before May 2019, for comparison.

In order to reproduce results in articles from a variety of sub-fields of the journal such as finance, accounting, marketing, operations management, organizations, strategy, and behavioral economics, we use a crowd-science approach (Nosek et al., 2012; Uhlmann et al., 2019) to leverage the expertise of many researchers in these different sub-fields. Overall, 733 volunteers joined the *Management*

¹Retrieved on August 22, 2023, from <https://pubsonline.informs.org/page/mnsc/datapolicy>.

Science Reproducibility Collaboration as reproducibility reviewers (see Appendix A for all names and affiliations), who together reportedly spent more than 6,500 hours on attempting to reproduce the results reported in the articles, using the replication materials and information provided by the article authors.

For articles subject to the 2019 disclosure policy, we find that when the reviewers obtained all necessary data (because they were included, could be accessed elsewhere, or no data were needed) and managed to meet the soft- and hardware requirements of the analysis, then results in the vast majority of articles (95%) were fully or largely reproduced.² However, in approximately 29% of the articles, datasets were unavailable either because they were proprietary or under a non-disclosure agreement (NDA), or because they originated in subscription data services to which reviewers did not have access. If we consider all assessed articles under the disclosure policy, then about 68% could be at least largely reproduced. Since data availability was by far the largest obstacle to reproducing results, the methodology used in an article is strongly correlated to its reproducibility. Namely, computational and simulation studies as well as online and laboratory experiments are more likely to be reproducible than field experiments, surveys, and other empirical studies. These differences in methodology and data availability are also the main drivers for substantial heterogeneity in reproducibility across the 14 departments of the journal.

Comparing these results to the period before the introduction of the mandatory disclosure policy, we observe a substantial increase in reproducibility. When code and data disclosure was voluntary, only 12% of article authors provided replication materials. Out of these selected articles, 55% could be (largely) reproduced.

The share of fully and largely reproduced results in our study appears high, in particular considering that the Code and Data Editorial team at the journal primarily assesses the completeness of replication materials, but does not attempt reproduction of the results themselves. That said, in addition to limited data availability, some replication materials suffered from insufficient documentation, missing code, or errors in the code, making reproduction impossible. For some studies, reviewers obtained different results and were not able to make out the reasons for the discrepancies. This implies that there is still room for improvement. We discuss implications for disclosure policies and procedures at *Management Science* and other journals in Section IV of this paper.

Our results complement findings in a recent literature on reproducibility and replicability in the social sciences. The definitions of these terms vary somewhat across studies, with some overlaps in their meaning (e.g., Christensen and Miguel, 2018; Dreber and Johannesson, 2023; Pérignon et al., 2023; Welch, 2019). “Replication” typically refers to verifying the results of a study using different datasets and different methods, thus exploring the robustness of results. The term “computational reproducibility” comes closest to the scope of our study, and is defined as the extent to which results

²We use the term “largely reproduced” when only minor issues were found and the conclusions from the analysis were not affected.

in studies can be reproduced based on the same data and analysis as the original study.³ Other types of reproducibility may consider recreation of analysis and data, or explore robustness to alternative analytical decisions (see also Dreber and Johannesson, 2023, for an in-depth discussion).

Recent systematic replication attempts of published results in the social sciences yielded replication rates of 36% in psychology (Open Science Collaboration, 2015, $N = 100$), 61% in laboratory experiments in economics (Camerer et al., 2016, $N = 18$), 62% in social science experiments published in *Nature* and *Science* (Camerer et al., 2018, $N = 21$), and 80% in behavioral operations management studies published in *Management Science* (Davis et al., 2023, $N = 10$).

In the field of economics, a number of studies targeting different sub-fields have set out to evaluate the computational reproducibility of results. The *Journal of Money, Credit and Banking* (JMCB) was one of the first journals to introduce a “data availability policy”, and one of the first ones to be evaluated. Dewald et al. (1986) assess the first 54 studies subject to the policy. Only eight studies (14.8%) submitted materials that were deemed sufficient to attempt a reproduction, and only four of these studies could be reproduced without major issues. As the authors put it, “inadvertent errors ... are a commonplace rather than a rare occurrence” (Dewald et al., 1986, p. 587). McCullough et al. (2006) examine JMCB articles published between 1996 and 2002, and successfully reproduce 22.6% of 62 examined works with a code and data archive, and only 7.5% considering all 186 relevant empirical articles in the journal. McCullough et al. (2008) report that for articles published between 1993 and 2003 in the Federal Reserve Bank of St. Louis Review, only 9 out of 125 studies (7.2%) with an archive could be successfully reproduced.

One of the top journals in economics, the *American Economic Review*, introduced a data and code availability policy in 2004, and other top journals followed. In examining this policy for studies published between 2006 and 2008, Glandon (2011) reports that among the studies with sufficient data archives, five out of nine studies (55.6%) could be reproduced without major issues. Overall, however, only 20 out of 39 sampled studies (51.3%) contained a complete archive, and for eight studies (20.5%) a reproduction was not feasible without contacting the authors.

More recently, Chang and Li (2017) attempt to reproduce articles in macroeconomics published between 2008 and 2013 across several leading journals, and successfully reproduce 22 out of 67 studies (32.8%). Gertler et al. (2018) examine the reproducibility of 203 empirical studies published in 2016 that did not contain proprietary or otherwise restricted data, and are able to reproduce 37% of them (but only 14% from the raw data). For 72% of the studies in the sample, code was provided, but executed without errors in only 40% of the attempts. Herbert et al. (2023) ask undergraduate economics students to attempt to reproduce 303 studies published in the *American Economic Journal: Applied Economics* between 2009 and 2018. Only 162 studies contained non-confidential and non-proprietary data. For these, 68 reproduction attempts (42.0%) were successful and another 69 (42.6%) were deemed partially successful. Pérignon et al. (2023) leverage a set of 168 replication packages produced in the

³Other scholars refer to computational reproduction also as verification (Clemens, 2017), verifiability (Freese and Peterson, 2017), or pure replication (Hamermesh, 2007; for an overview see also Ankel-Peters et al., 2023).

context of an open science multi-analyst study in empirical finance (see Menkveld et al., 2023). Out of 1,008 hypothesis tests across all materials, 524 (52.0%) were fully reproducible, with another 114 (11.3%) yielding only small differences to the original results.

Reproducibility studies in other related fields show similarly limited reproducibility. For a sample of 24 studies subject to the *Quarterly Journal of Political Science*'s data and code review, Eubank (2016) finds that only 4 (16.7%) did not require any modification in order to reproduce the results. In genetics, Ioannidis et al. (2009) report that only 8 out of 18 microarray gene expression analyses (44.4%) were reproducible. An analysis of biomedical randomized controlled trials yields 14 out of 37 (37.8%) successfully reproduced studies (Naudet et al., 2018). Artner et al. (2021) attempt to reproduce the main results from 46 published articles in psychology with the underlying data but no code, and were successful in 163 out of 232 statistical tests (70.3%). Xiong and Cribben (2023) examine the reproducibility of 93 articles using fMRI published in prominent statistics journals between 2010 and 2021, of which only 23 (24.7%) included the actual dataset, and 14 (15.1%) could be fully reproduced.

A comparison of reproducibility rates across different studies is difficult. Different studies often apply different definitions and standards of reproducibility, and reasons for non-reproducibility may differ between different journals due to different policies and enforcement procedures, and different methods and data availability conditions in their fields. For example, our share of 95% of (largely) reproduced articles (conditional on data being available to the reviewer and hard- and software requirements being met) appears to be in a similar ballpark as the 85% of at least partially successful reproductions at the *AEJ: Applied Economics*. However, while both journals have similar disclosure policies, in the respective time periods replication materials of articles at *AEJ:AE* only underwent a cursory review while the Code and Data Editorial Team at *Management Science* checked all replication packages for completeness.

In recent years, there have been significant developments in the institutional arrangements for reproducibility of journal articles. For economics, Vlaeminck (2021) reports that in a sample of 327 journals, 59% have data availability policies, a significant increase compared to 21% in the year 2014. Similar developments are present in the fields of business and management. For example, several other journals published by INFORMS have adopted similar code and data disclosure policies after *Management Science* took the lead in 2019. At the time of writing this paper, 20 out of the 24 journals used for the UT Dallas Business School rankings have a code/data disclosure policy, but only 10 made code/data sharing compulsory, and only two have a code and data editor enforcing the policy.⁴ Colliard et al. (2023) discuss journals' incentives with respect to reproducibility, and Höffler (2017) provides evidence that in economics, journals with disclosure policies are more often cited than journals without such policies.

⁴For comparison, out of the top 25 journals in the 2022 Scimago ranking in Economics and Econometrics, 23 have code/data policies, 17 require that code/data are shared, and 6 have code/data editors. There is some overlap of this set of journals with the UT Dallas list.

The ability to reproduce results reported in published articles by executing the code on the data, both provided by the authors, does not, by itself, guarantee that results are replicable. But it does provide a useful baseline. It increases confidence that reported results could, in principle, be replicated. Allowing access to original code and data also makes it possible for independent research teams to scrutinize robustness, conduct their own analysis including meta-analytical work spanning multiple studies and datasets, reuse code in other research, and either build on the results or design studies to show the limitations of original results. The ability to do this promotes scientific discourse, and importantly, also decreases incentives for academic fraud and data falsification.

II STUDY DESIGN AND PROCEDURES

II.A Procedures

Prior to 2019, *Management Science* encouraged but did not require the disclosure of data for submitted/accepted manuscripts. In June 2019, a new policy was established, which applied to all newly submitted manuscripts and is still in effect at the time of this writing. The policy requires that all code and data associated with accepted manuscripts at *Management Science* have to be provided before the manuscript goes into production, but it also allows some exceptions, in particular licensed data (Compustat, CRSP, Factset, WRDS, etc.), proprietary data, or confidential data under a NDA. In these cases, detailed descriptions of data provenance and dataset creation are expected. The journal established the position of a Code and Data Editor (CDE) and consequently positions of Code and Data Associate Editors (CDAEs), who review all replication packages for completeness before an article goes into production. However, the CDE and CDAEs are volunteer positions, so there are limits to a complete check of the packages of all accepted articles for reproduction.⁵

Our study, pre-registered at the Open Science Framework,⁶ attempts to assess the reproducibility of articles published in *Management Science* before and after the introduction of the 2019 policy, based on the materials provided by the authors. For the period after the policy change, our initial sample consists of 447 articles⁷ that fell under the disclosure policy introduced in June 2019, had been reviewed by the CDE team through January 2023, and were published (with their compulsory replication package) on the journal’s website. As a comparison sample we chose all 334 articles that were accepted at the journal between January 2018 and April 2019, and would have fallen under the disclosure policy (i.e., include code or data) but were accepted before the announcement of the policy and were thus not

⁵If code and data are included, the CDE team also attempts to run the code, but without verifying outputs. As a contrasting example, the American Economic Association employs a different model with a paid Data Editor position including a budget for administrative and research assistants, where all replication packages for all AEA journals are fully reproduced before a final acceptance decision is made.

⁶The pre-registration can be found at URL <https://osf.io/mjqg5>. Unless otherwise noted, we followed our pre-registered procedures.

⁷In our pre-registration we mention 450 articles, but during the review phase we noted that 3 of these articles did not fall under the disclosure policy, reducing the initial sample to 447.

subject to the policy (which only applied to articles initially submitted after June 1, 2019).⁸ Out of those 334 articles, for 42 the authors had voluntarily provided a replication package, which entered our project reviews. Thus, the size of our initial sample of replication packages to be reproduced is 489.

On January 12, 2023, the Editor-in-Chief of *Management Science* wrote an email to all 9,762 reviewers who provided a review to the journal in the past 5 years, introducing the project and inviting them to serve as reproducibility reviewers (see Appendix E.1). In addition, the invitation to participate in the project was sent via professional mailing lists (e.g., Behavioral Economics, Finance, Marketing). In total, 927 researchers completed an initial reviewer survey asking for their research fields (namely, to which *Management Science* departments they would typically submit their manuscripts) and their familiarity with different analysis software/frameworks and databases (see Appendix E.2).

The assignment of articles to reviewers proceeded over two main assignment rounds and a consecutive third round. In the first assignment round at the beginning of February 2023, we attempted to find a reviewer for each of the 489 packages out of the 927 reviewers. We applied the Hungarian method (Kuhn, 1955) that tries to maximize the match with penalties for mismatches in department, software skills, and database access, and random resolution of ties (see Hornik, 2005, for the R implementation). These matches were then manually assessed for potential conflicts of interest (e.g., reviewer and author in the same department), in which case article and reviewer were removed from the match and re-entered the “pools” of articles and reviewers. Once the match was completed, all reviewers received an email informing them of their assignment, with links to the article, the supplementary materials page, and to guidelines for reviewers. Reviewers were also asked to either confirm their assignment, or to contact us to indicate any conflicts of interests or other reasons that they could not provide a report for the assigned article. These cases were also added back to the pool.

After two weeks, we ran a second assignment round. For articles, the sample consisted of previously unmatched articles (which received priority) and a second set of all articles (to find a second reviewer for many of them). All reviewers with no assignment yet entered the match. We once again used the Hungarian method with moderate penalties for department and software mismatches and prohibitive penalties for assignments of the same article or previous assignments, and random resolution of ties. The resulting match was screened for conflicts of interests. As before, reviewers received their assignment by email, and any reported mismatches or conflicts were tracked. A few dropouts of reviewers were recorded, otherwise articles and reviewers re-entered the “pool”. Reviewers who did not confirm their assignment in the first or second round received a reminder email at the end of February.

The third round of assignments, from the beginning of March 2023, was run continuously in several waves and mostly manually. Once a sufficient mass of articles (rejections of assignments, leftover articles who have not received their second assignment yet) and reviewers (unmatched reviewers, or reviewers available for another report) was reached, for each article a list of all possible compatible

⁸Note that we thus deliberately did not include articles in our study that were accepted after the introduction of the 2019 policy but were not subject to it because they were originally submitted before the introduction. For these articles, their authors could have falsely assumed that the new disclosure policy applies while it did not, thus biasing our assessment of the effect of the policy.

reviewer matches was compiled, and out of this one reviewer was assigned. As before, reviewers were informed about their match and asked to confirm their assignment.

Reviewers were asked to make an honest attempt to a reproduction of the article’s main results (figures, tables, and other results in the main manuscript) solely based on the provided replication materials (and not to contact the original authors of the articles, see also McCullough et al. 2006, for similar approaches) and to provide their report within about 5 weeks (though we also accepted late entries). Reviewers submitted their report through a structured survey implemented in Qualtrics (see Appendix E.3). They also received detailed guidelines (see Appendix E.4), providing definitions for different reproducibility assessment outcomes and explanations for all survey fields. The survey asked for an overall assessment, information about the content of the replication package (readme, data, code, etc.) and their quality, individual reproducibility assessment of all results tables and figures as well as other results reported in the manuscript, as well as assessments of time spent, of their own expertise in research field and analysis methods, and of their expectation of the replicability (as opposed to reproducibility) of the article. Reviewers were also asked to provide evidence of their reproduction attempts in the form of log files or screenshots.

During the whole review period, we answered any questions by reviewers by email. Once a significant number of reviews had been collected, we checked them for completeness and consistency. Where necessary, we followed up with reviewers to clarify questions and resolve inconsistencies.⁹ All in all, we followed up on about 13% of all reports.

In late September 2023, we wrote emails to all corresponding authors of the articles for which we obtained reports, and provided them with the reports (redacted for anonymity). Authors could submit a short comment of up to 2,000 characters on each report, which was then included in our dataset.¹⁰ 115 authors or author teams made use of this possibility and submitted comments.

II.B Final Sample

In total, we received 753 reports from 675 reviewers and reviewer teams, who spent in total more than 6,500 hours on this project.¹¹ We allowed reviewers to enlist the help of a colleague as a secondary reviewer, so for 61 reports reviewers are actually teams of two persons. While 599 reviewers provided one report each, 74 reviewers provided reports for two different articles, and two reviewers for three articles.

⁹E.g., a reviewer may indicate that log files are provided, but did not verify whether they are consistent with the results. In other cases, the overall assessment of a replication package may not have been consistent with the individual assessments of tables and figures. Some reviewers could initially not find the replication package because the respective link was missing on the journal’s webpage, and we provided them with the correct links.

¹⁰In addition, the journal allows authors to submit an improved replication package, which will replace the previous (reviewed) replication package on the journal’s replication server. We note, however, that our analysis is only based on the original replication materials.

¹¹Two reviewers entered unrealistically high numbers of more than 160 hours (4 working weeks); we set these observations to “missing” in our dataset. The median reviewer spent 4 hours.

Table 1 shows that a majority of reviewers are at an intermediate stage in their academic career, at the Associate Professor, Assistant Professor, or Postdoc level. About one in seven reviewers was a full professor, and about the same number are PhD students. In addition, there are reviewers working in other roles at research and professional institutions. Across these career levels, reviewers differ in their frequency of enlisting a secondary reviewer (with Full or Associate Professors being more likely to do so, while almost all PhD students worked alone) and the time spent (differences there are mainly driven by whether it was a team or not). However, they do not differ much in their self-assessed expertise in the method or topic of the article. In our analysis below, we also did not find any systematic differences across reviewer characteristics in terms of assessment outcomes or other report characteristics.

TABLE 1: REVIEWER CHARACTERISTICS

$N = 675$	Share	Enlisted 2nd reviewer	Avg. Hours Spent	Avg. Expertise Method (0-100)	Avg. Expertise Topic (0-100)
Professor	14%	21%	13.1	84.3	60.8
Associate Professor	26%	11%	8.3	83.2	61.5
Assistant Professor/Postdoc	40%	6%	8.4	84.1	58.7
PhD student	16%	1%	9.0	83.8	59.2
Other	4%	3%	6.1	82.8	52.7

Table 2 gives an overview of our final sample of assessed articles. Out of the 781 articles, 292 from before the introduction of the 2019 policy had no replication package, so are not assessed. For 30 articles with replication packages, we could not find a suitable reviewer, and thus cannot report any reproducibility results.¹²

TABLE 2: INITIAL AND FINAL SAMPLE OF ARTICLES AND REPORTS

	Before 2019 policy	After 2019 policy	Total
Initial sample of articles	334	447	781
Articles with replication package available	42	447	489
Articles with package and report(s)	40	419	459
1 report	16	149	165
2 reports	24	270	294

¹²These 30 articles are not part of the analysis. We observe little evidence of selection issues. Table B.1 in Appendix B compares the software requirements of the 30 articles without a report and the 459 articles with at least one report. It seems that articles where we could not find a suitable reviewer were less likely to use the most common software Stata and more likely to use one of the less often used software. Still, these differences are statistically not significant at the 5%-level (Fisher Exact test, two-sided, on the frequency of Stata and frequency of “Other” software).

TABLE 3: FIELDS OF ASSESSED ARTICLES AND REVIEWERS

<i>Management Science</i> Department	Abbr.	Share of Articles ($N = 489$)	Share of Reviewers ($N = 675$)
Finance	FIN	27.4%	24.3%
Behavioral Economics and Decision Analysis	BDE	18.4%	30.1%
Accounting	ACC	12.5%	8.2%
Operations Management	OPM	9.2%	7.1%
Marketing	MKG	5.7%	6.5%
Revenue Management and Market Analytics	RMA	4.7%	0.7%
Information Systems	INS	4.3%	4.0%
Business Strategy	BST	3.3%	4.6%
Healthcare Management	HCM	3.3%	1.9%
Big Data Analytics/Data Science	BDA	3.1%	3.4%
Organizations	ORG	3.1%	3.6%
Entrepreneurship and Innovation	ENI	2.3%	4.0%
Optimization	OPT	1.4%	1.2%
Stochastic Models and Simulations	SMS	1.4%	0.4%

In Table 3 we list the *Management Science* departments where the articles in our final sample appeared.¹³ This distribution is representative for articles in the journal, with Finance, Behavioral Economics and Decision Analysis, Accounting, and Operations Management being the largest fields. To facilitate the matching of reviewers and articles, upon registration we asked reviewers to which department(s) they would most likely send one of their articles. Table 3 shows the distribution of the first-named department. This distribution follows largely the distribution of articles, with the exception that researchers from Behavioral Economics and Decision Analysis contribute disproportionately.¹⁴ During code and data review the CDE team usually classifies articles into one of five categories according to their main methods. While about one-fifth of the articles in the sample mainly use simulations or computations (and thus often do not rely on data), almost 60% of the articles in our sample are based on empirical data (primary or secondary datasets that do not originate from experiments or surveys), with the remaining articles discussing laboratory or online experiments (15%), field experimental data (4%), or data from surveys (3%).

II.C Reviewer consistency and aggregation

In order to obtain information on potential variability in reproducibility assessments, we aimed to get not just one but two reports for as many articles/replication packages as possible. We succeeded in obtaining two reproducibility reports for 294 articles. For 59% of these articles, both reviewers chose

¹³There have been some changes in the structure of departments at the journal over the past years. In case departments were changed or merged, we classified articles by the current (successor) department.

¹⁴One reason for this might be a higher awareness for the issues of reproducibility and replicability in this field. Another reason could be that most of the primary authors of this reproducibility study come from this research area.

the exact same overall assessment. When only considering whether a reviewer classified an article as at least largely reproducible, or not, then the agreement rate is 86%. For the overall assessment of reproducibility, reviewers seem to mostly differ on whether some minor issues are worth mentioning (in generally reproducible studies), and whether a few results that can be recovered are sufficient to deem a study “Largely reproduced” rather than “Not reproduced.” Otherwise, differences may result from whether reviewers obtained access to datasets, managed to run the code in the appropriate software environment, or how much effort they put into the reproduction.¹⁵

In our analysis presented in the next section, we aggregated assessments at the article level. Specifically, if both reviewers chose the same overall assessment, we select one report randomly. If we have two reports for an article, we select the report with the higher reproducibility assessment. This is based on the expected error structure in assessments. When one reviewer could obtain the data or run the software but the other reviewer could not, then the former’s more informed reproducibility judgement should be at least as positive as the latter’s. Similarly, while random reviewer errors in assessing the results may lead to a lower reproducibility classification, it is unlikely that those errors yielded exactly the results also obtained by the original authors. And since reviewers had to document their reproducibility efforts and upload log files or screenshots, it seems unlikely that they would have incentives to overstate an assessment result.

We note that our approach in using the higher assessment of multiple reviews is in line with other reproducibility studies, e.g., Herbert et al. (2023). At the end of the next section we discuss the robustness of our results to using other aggregation rules or analyzing the data at the level of individual figures and tables, with detailed results included in Appendix C.

III RESULTS

III.A Main results

In addition to individual reproducibility assessments of tables, figures, and other results, we asked reviewers for an overall assessment of their reproduction attempt. The guidelines given to reviewers stated the following assessment classifications:

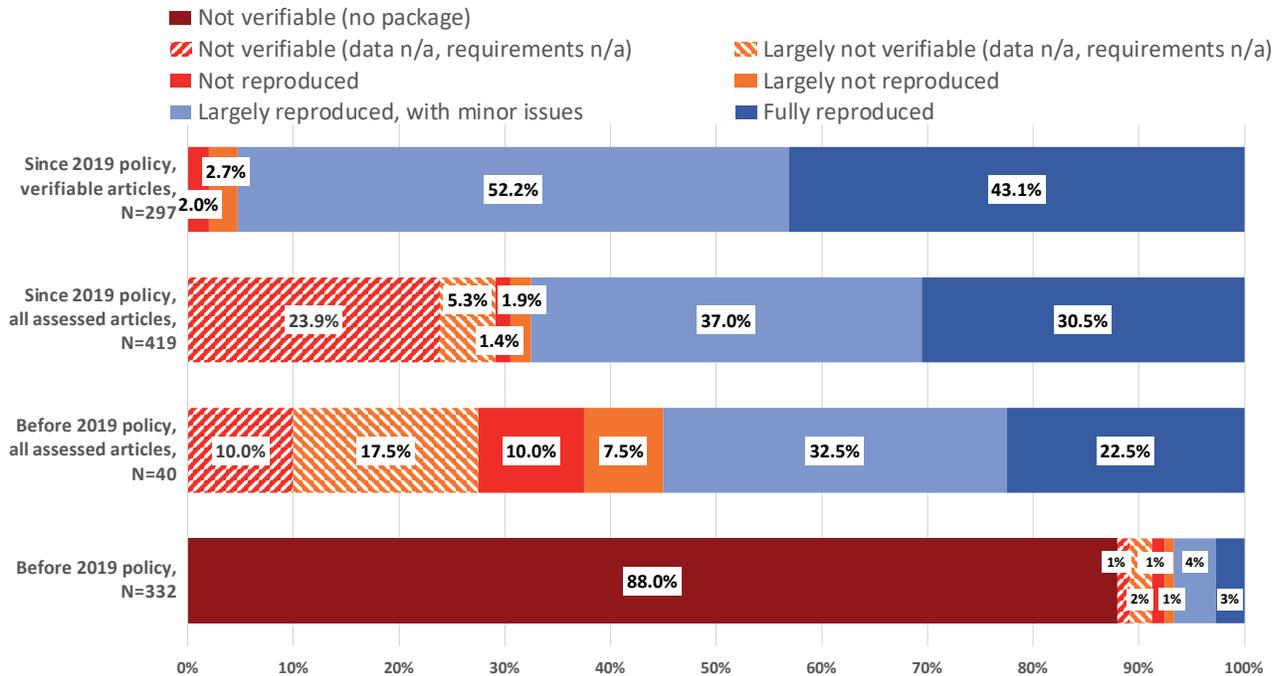
- An assessment of “Fully reproduced” means that the output of the reproduction analysis shows the exact same results as reported in the article, for all results reported in the main manuscript.
- “Largely reproduced, with minor issues” means that there may be small differences in the reproduction output compared to the results in the original article, but the article’s conclusions and learnings stay the same.

¹⁵In Appendix D we provide more details on variability in reviewer assessments.

- “Largely not reproduced, with major issues” means that there are major differences in the output compared to the results in the article, such that the reproduction results could not be used to support the conclusions of the original article.
- An assessment of “Not reproduced” means that the results from the reproduction cannot support the conclusions drawn in the paper, either because the output is different, or because the results cannot be produced at all because of missing data or non-recoverable code.

We note, however, that equipped with these guidelines, the eventual categorization of the article remains subjective to the reviewer. For all overall assessments of “Largely not reproduced” and “Not reproduced”, we reviewed the individual reports to distill the main reasons for limited reproducibility. Consequently, cases where the reviewer was not able to get access to a required dataset or could not meet the software and hardware requirements of the analysis were labeled “Not verifiable” and “Largely not verifiable” rather than “Not reproduced” and “Largely not reproduced”, respectively.¹⁶

FIGURE 1: OVERALL ARTICLE REPRODUCIBILITY ASSESSMENTS, BY POLICY



Based on these classifications, Figure 1 presents our main outcomes. The upper two panels show reproducibility assessments for articles that were subject to the disclosure policy introduced in 2019, while the lower two panels pertain to articles that were accepted before that policy. The first panel shows the distribution of assessments conditional on reproducibility being verifiable. Among these articles, 95.3% could be classified as fully reproduced or largely reproduced. However, for 29% of

¹⁶We note that this qualification of assessments was not yet anticipated in our pre-registration.

assessed articles, reviewers could not obtain the dataset, and in 1% the hard- and software requirements could not be met (e.g., software could not be installed, or the code would run for an untenable amount of time). Also in these cases, reviewers were not able to reproduce the results. The second panel in Figure 1 includes these cases, displaying results for all assessed articles. The share of articles that our reviewers were able to fully or largely reproduce is 67.5%.

The third panel of Figure 1 shows the overall assessments for the 40 articles from the time before the 2019 disclosure policy was introduced, for which replication materials were available. Our reviewers could reproduce or largely reproduce the results of 55% of these articles.¹⁷ In the fourth panel of Figure 1, we include all 332 articles from our sample of articles accepted before the 2019 disclosure policy. Considering those articles that do not voluntarily provide replication materials as not reproducible reduces the share of at least largely reproduced articles to 6.6%.¹⁸

TABLE 4: REGRESSING REPRODUCIBILITY ON DISCLOSURE POLICY EXISTENCE

Model	(1)		(2)		(3)	
	All incl. no package		All with package		All verifiable	
Sample of articles	Coeff	StdErr	Coeff	StdErr	Coeff	StdErr
Constant	0.066***	(0.021)	0.550***	(0.075)	0.759***	(0.045)
Disclosure Policy	0.609***	(0.028)	0.125	(0.078)	0.194***	(0.047)
Observations	751		459		326	
R^2	0.379		0.006		0.051	

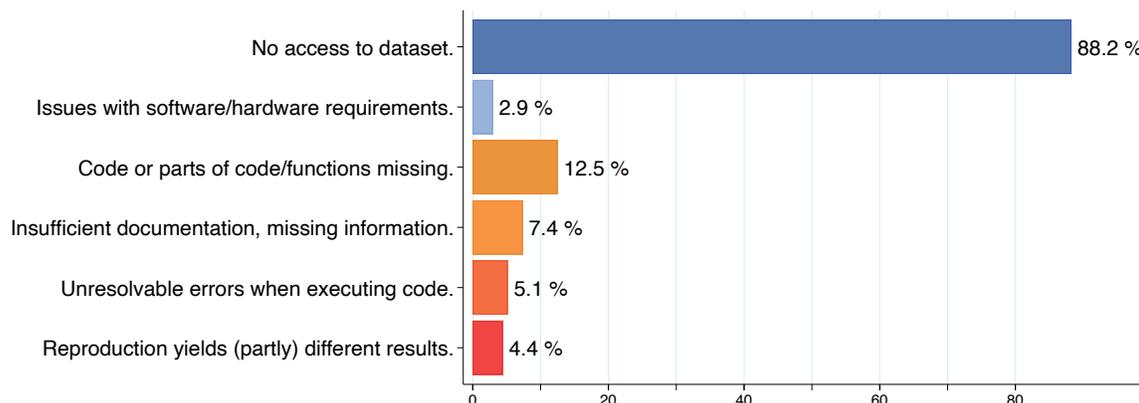
Notes: The dependent variable is a binary indicator whether the article was classified as “fully reproduced” or “largely reproduced”, or not. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

Results from linear probability models, displayed in Table 4, lend statistical support to the positive change since the introduction of the data and code disclosure policy. In Model 1 we regress whether an article could be at least largely reproduced or not on the policy dummy for all articles in our sample (i.e., we are comparing the second and the fourth panels in Figure 1), indicating that after the introduction of the policy, a randomly chosen article is 61% more likely to be reproduced. In Model 2 we restrict our attention to the sample of articles for which a replication package was provided (i.e., comparing the second and the third panel in Figure 1). In this regression, the coefficient for the policy is positive but statistically not significant ($p = 0.109$). Finally, Model 3 focuses on all articles which are considered verifiable (i.e., comparing the second and the third panel in Figure 1 but without the

¹⁷We note, however, that these 40 out of 332 articles are heavily selected: authors voluntarily provided a replication package while being encouraged but not required by the journal. More than 50% of these articles were published in the BDE department, and none of them belonged to the Finance department, indicating selection also on availability of data.

¹⁸One may argue that when replication materials are not voluntarily provided to the journal, they may still be hosted on authors’ personal websites or in other archives. For a random sample of 50 out of 292 articles without replication package, we searched all author websites as well as repositories for replication materials, and we found none.

FIGURE 2: REASONS FOR NON-REPRODUCIBILITY FOR ARTICLES SINCE 2019 POLICY



non-verifiable articles). The policy coefficient indicates that conditional on data being available and hard- and software requirements being met, articles are 19% more likely to be reproducible after the introduction of the disclosure policy.¹⁹

The unavailability of data is one of the major impediments for reviewers to reproduce an article. A dataset may be unavailable, for example, because the reviewer does not have a subscription to the commercial provider, because the dataset was collected under NDA with the involved company, or because the dataset contains sensitive information (e.g., on personal health or illegal activity). For the sample of 136 reviewed articles falling under the disclosure policy that were classified as either “Not reproduced” or “Largely not reproduced”, Figure 2 displays the main reasons we identified for the reviewers’ failure to reproduce.²⁰

Limited access to the dataset was a reproducibility barrier for 88% of non-reproducible articles, and the time needed to run the code, complexity of the code, or issues with installing the software environment were the reason for non-reproducibility of another 3%. Other reasons included the non-availability of code or functions (13%), insufficient or missing documentation (7%), or unresolvable errors when executing the code (5%). For 4% of the non-reproducible or largely not reproducible articles, the main reason for this assessment was that the reproduction yielded partly different results than reported in the article.²¹

¹⁹We obtain the same conclusions employing corresponding Probit/Logit models or Fisher Exact tests. We note that strictly speaking, our data does not allow to imply a causal effect of the disclosure policy. Authors’ attitudes towards making their research reproducible may have independently changed over time, just as the intensity of policy enforcement at the journal may have varied. Older replication packages may be less reproducible due to software changes. The introduction of the policy does not have features of a natural experiment, and our sample only spans a relatively short (and interrupted, see Footnote 8) time period.

²⁰Note that multiple issues may apply to the same article.

²¹In Table B.2 in Appendix B we contrast these numbers with the reasons for non-reproducibility for articles which voluntarily provided replication packages before the 2019 disclosure policy took effect. Although the sample size for this period is low ($N = 18$), it appears that reasons for non-reproducibility of voluntarily provided packages are less likely to be missing data and more likely to be issues with missing or non-working code. Reproducibility for older materials may also be affected by limited backward compatibility of statistical software, sometimes producing different results. The reviewers in our study did not report such issues, but they may be more relevant when comparing more distant time frames.

Since many authors cannot include the original data in their replication packages for various reasons, in such cases the Code and Data Editor at the journal started to encourage the provision of log files that can show that the analysis code works and produces the desired results. Correspondingly, about 52% of the articles classified as “Not verifiable” or “Largely not verifiable” included log files for all results in the replication package, and further 24% included log files for at least some results. Consequently, 60% of (largely) not verifiable articles were assessed as “Not reproduced but consistent with log files” (84% of those that provided all log files, and 66% of those that provided at least some logs).

III.B Variation in reproducibility

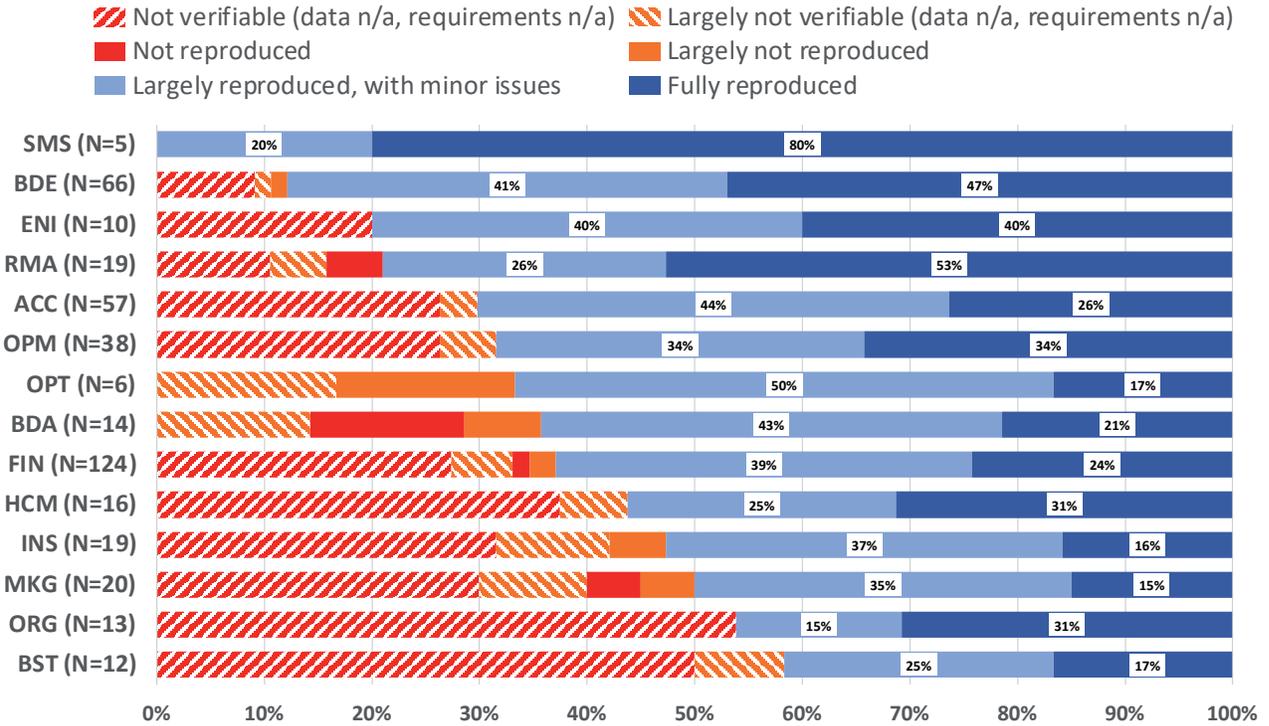
Our data allows us to break down the reproducibility of articles published under the disclosure policy to the level of research fields and types of research. Figure 3 shows the reproducibility assessments across the 14 *Management Science* departments. We observe considerable heterogeneity in the share of reproduced or largely reproduced articles across the different fields, ranging from 42% to 100%. Note, however, that there are substantial differences in the number of published articles across departments. Also, data availability may vary drastically between different fields.

While many studies in the department Behavioral Economics and Decision Analysis (BDE) rely on primary data from experiments, other fields often use proprietary data from subscription databases (e.g., Compustat, CRSP, WRDS), or confidential and sensitive data that cannot be shared with other researchers (e.g., field experiments with companies, health care data, or sensitive surveys). In Figure 4, we distinguish reproducibility outcomes by the primary type/method of the article, as classified during the journal’s code and data review. We indeed observe significant differences in the reproducibility outcomes across articles employing different methods. All studies reporting on laboratory and online experiments include their dataset, making them highly reproducible. Most studies running simulations or other computations, mostly embedded in theoretical articles, do not rely on datasets, making them highly reproducible. On the other hand, many empirical studies with primary or secondary datasets rely on proprietary or subscription data, making them less reproducible if reviewers have no access to these datasets. Field experiments in business fields often run under NDAs, and survey studies may include sensitive data that cannot be shared (sometimes even ethics committees restrict the publication of datasets).²²

In Table 5 we report three linear probability models in which we assess this heterogeneity statistically. The outcome variable in all three models is a dummy indicating whether an article is classified as fully or largely reproduced, or not. In Model (1), we regress reproducibility on department fixed effects, with the baseline being the Finance department (FIN), with a sizable sample size and close to the average reproducibility level. We observe that the SMS and BDE departments have significantly higher reproducibility rates than the Finance department, while the other departments do not differ significantly from Finance. In Model (2), we regress the same outcome on article type fixed effects,

²²Table B.3 in Appendix B demonstrates the variation of paper types/methods across the different departments of the journal. In the table, we ordered departments and methods by their reproducibility to highlight the correlation.

FIGURE 3: OVERALL REPRODUCIBILITY ASSESSMENTS BY JOURNAL DEPARTMENT



Note: Department acronyms are SMS: Stochastic Models and Simulations, BDE: Behavioral Economics and Decision Analysis, ENI: Entrepreneurship and Innovation, RMA: Revenue Management and Market Analytics, ACC: Accounting, OPM: Operations Management, OPT: Optimization, BDA: Big Data Analytics/Data Science, FIN: Finance, HCM: Healthcare Management, INS: Information Systems, MKG: Marketing, ORG: Organizations, BST: Business Strategy.

FIGURE 4: OVERALL REPRODUCIBILITY ASSESSMENTS BY ARTICLE TYPE/METHOD

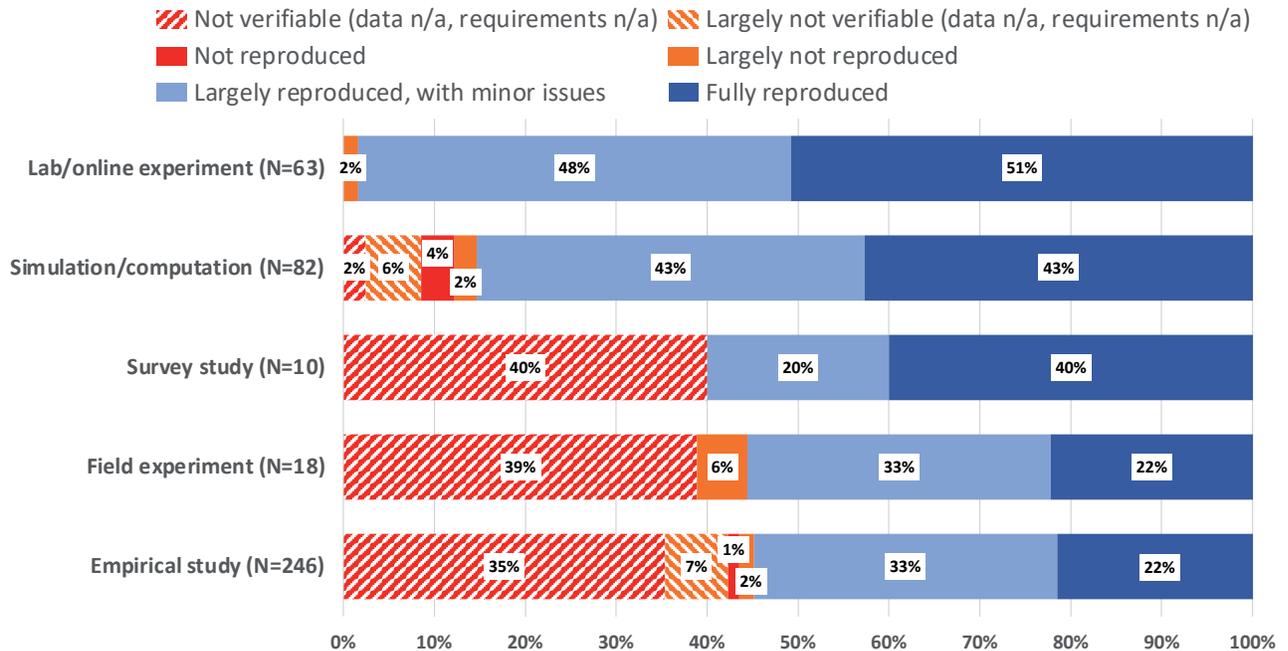


TABLE 5: REGRESSING REPRODUCIBILITY ON JOURNAL DEPARTMENT AND ARTICLE TYPE

Model	(1)		(2)		(3)	
	Coeff	StdErr	Coeff	StdErr	Coeff	StdErr
Constant	0.629***	(0.041)	0.600***	(0.138)	0.630***	(0.146)
SMS	0.371*	(0.209)			0.034	(0.207)
BDE	0.250***	(0.070)			0.019	(0.087)
ENI	0.171	(0.151)			0.215	(0.143)
RMA	0.160	(0.113)			-0.110	(0.118)
ACC	0.073	(0.073)			0.128*	(0.070)
OPM	0.055	(0.085)			-0.049	(0.083)
OPT	0.038	(0.192)			-0.299	(0.191)
BDA	0.014	(0.129)			-0.323**	(0.137)
HCM	-0.067	(0.122)			-0.059	(0.115)
INS	-0.103	(0.113)			-0.073	(0.108)
MKG	-0.129	(0.111)			-0.118	(0.106)
ORG	-0.167	(0.134)			-0.120	(0.127)
BST	-0.212	(0.139)			-0.188	(0.134)
Lab/Online Experiments			0.384**	(0.149)	0.336**	(0.153)
Simulation/Computation			0.254*	(0.146)	0.336**	(0.155)
Field experiment			-0.044	(0.172)	-0.009	(0.173)
Empirical study			-0.051	(0.141)	-0.087	(0.143)
Observations	419		419		419	
R^2	0.072		0.140		0.180	

Notes: The dependent variable is a binary indicator whether the article was classified as “fully reproduced” or “largely reproduced”, or not. Baseline is the Finance department, and survey studies. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. Department acronyms are SMS: Stochastic Models and Simulations, BDE: Behavioral Economics and Decision Analysis, ENI: Entrepreneurship and Innovation, RMA: Revenue Management and Market Analytics, ACC: Accounting, OPM: Operations Management, OPT: Optimization, BDA: Big Data Analytics/Data Science, FIN: Finance, HCM: Healthcare Management, INS: Information Systems, MKG: Marketing, ORG: Organizations, BST: Business Strategy.

with articles based on surveys as the baseline. We find that while field experiments and empirical studies (other than experiments or surveys) do not differ from survey studies in their reproducibility, lab/online experiments and articles featuring simulation/computation are significantly more likely to be reproducible. Finally, in Model (3), we include both department and article type fixed effects. The coefficients for article type are not much affected by including department fixed effects, while vice versa there are some sizable changes. Once accounting for the article type/method used, articles in departments SMS and BDE are not significantly more reproducible anymore compared to other departments, namely Finance. On the other hand, controlling for methods, articles in the Accounting (ACC) department are significantly more reproducible than articles in Finance (more often including

the data set), and articles in the field of Big Data Analytics (BDA) are less reproducible (as datasets are often not included or accessible).

III.C Robustness

In the analysis above we only considered reproducibility assessments at the article level, taking the higher assessment if two reports were available for an article. To examine the robustness of our results, we also examine the reproducibility for different aggregation rules, at the level of individual reports, and at the level of tables, figures, and other results.

In Appendix C, Table C.1 reports distributions of overall assessments when choosing the report with the lower assessment whenever there are multiple reports for an article, and when randomly selecting one of two reports (with 10000 repetitions). Since in our aggregation above we selected the report with the higher reproducibility assessment, these data show somewhat lower reproducibility levels. However, the differences are rather small. E.g., compared to the 95.3% (largely or fully) reproduced results for verifiable articles reported above, we observe 91.4% when taking the lower assessment of multiple reports, and 93.8% when randomizing which of two assessments is considered.

The regressions reported in Table C.2 are based on all reports rather than just one report per article, clustering standard errors at the article level. Their results mirror the results on policy effects reported in Table 4 above. Overall, the same reproducibility patterns emerge: the main reason for non-reproducibility is data access, departments differ widely in their reproduction rates, but that is to a large extent driven by different methods being used across departments.

Appendix C also reports and discusses the assessment results for individual tables, figures, and other results (e.g., statistical tests reported in the manuscript texts). As to be expected, these individual results are highly correlated with the overall assessments. For example, in reports that reached an overall assessment of “Fully reproduced”, 99.1% of individual tables and 99.7% of individual figures were classified as largely or fully reproduced. When the overall assessment was “Not reproduced”, only 2.7% of tables and 7.5% of figures could be reproduced, on average.

IV DISCUSSION AND CONCLUSION

In this study we undertake a comprehensive assessment of the reproducibility of results in *Management Science*. With the collaborative efforts of over 700 reviewers we examine nearly 500 articles to assess the computational reproducibility of their results. For articles published since the introduction of the 2019 disclosure policy, the good news is that more than 95% of articles could be fully or largely computationally reproduced, when data accessibility and hardware/software requirements were not obstacles for reviewers. This appears commendable. However, reviewers faced data accessibility challenges for approximately 29% of the articles in our sample, and the overall rate of successful reproduction is reduced to 68% when considering such articles as non-reproducible. Relatedly, differences in methods and dataset accessibility also drive heterogeneity in reproducibility rates across different fields.

This makes data availability a central issue in reproducibility. To improve the credibility of research within business and management, efforts should be directed toward facilitating data access and sharing. Strictly restricting a journal in the area of business, economics, and management to only articles that can freely share their data seems unrealistic and would exclude valuable research from being published. Instead, other arrangements may need to be found for such cases. Approaches could include, among others,

- the inclusion of de-identified data in the replication package, only useful for reproduction but not for new original research;
- agreements with subscription databases for access for reproduction purposes via the journal;
- providing access to datasets through special infrastructure that limits use to specific purposes (similar to platforms used by government agencies to provide micro data); or
- sharing data only with a journal’s code and data editor or with a third-party agency which then certifies reproducibility.

In addition, human subjects ethics committees may need to be sensitized to also consider the ethics of research transparency in their deliberations, to find compromises that at the same time ensure human participant privacy and allow for the full reproduction of research results. Data access limitations also touch upon important questions of fairness and bias: with proprietary, non-open datasets, certain research results may only be obtained by privileged researchers, with the data provider serving as a gatekeeper with potential conflicts of interest.

Our study underscores the value of large-scale reproducibility assessment projects. We provide an assessment of the current state of affairs in the field of business and management, and thus contribute to drawing a realistic picture of the overall credibility of research in the field. Repeating such assessments will serve as a form of quality control for newly developed journal policies and procedures. The project showcases best practices and may help developing standards for replication materials, but also identifies major gaps and weaknesses in current policies that need to be addressed. Our results can influence journal and funding agency policy decisions. The active participation of more than 700 reviewers who invested significant time and effort in reproducing results highlights the commitment in the community to improving scientific rigor. In an ex-post survey, quite a few of our reviewers reported that their participation was a great learning experience, in particular with respect to preparing their own future replication packages. Informed about the assessments of their articles, most authors appreciated the reviewers’ comments, and many voluntarily provided improved versions of their replication packages that address the reviewer comments. Thus, this project also raised awareness of reproducibility issues, furthering a culture of open science, and potentially also the quality of (existing and future) replication materials.

That said, our study also sheds light on the significance of journal code and data review procedures. We observe that the introduction of the 2019 disclosure policy is associated with a significant increase in

the reproducibility of articles in *Management Science*. When code and data disclosure was voluntary, only 12% of authors submitted replication materials (out of which 55% could be at least largely reproduced). This suggests that the policy’s effect is largely driven by increasing the mere *verifiability* of articles. However, there is still room for significant improvement. Smaller scale changes could be targeted towards improving the current process, such as increasing incentives for authors to provide proper replication packages right away by making the acceptance decision conditional on replication package approval; or integrating the code and data review process into the manuscript handling system to make it more efficient and transparent.

A more comprehensive reevaluation of code and data review procedures, however, may foster the pivotal role that code and data review plays in ensuring research reproducibility more effectively. In particular, large-scale reproducibility projects such as the present study may become obsolete if the journal puts resources and processes into verifying reproducibility already upon publication of an article. In the current institutional setup, the Code and Data Editor at *Management Science* and his team of Associate Editors are volunteers with naturally limited capacity to conduct comprehensive reproduction. To that end, different institutional arrangements may be advisable:

- Similar to the institutional setup at the American Economic Association (see Vilhuber, 2019), code and data review could be professionalized by introducing the position of a (half- or full-time) paid Code and Data Editor, with appropriate budget for assistance and software and data access.
- Code and data review, and reproducibility certification could be delegated to a third-party agency that conducts these activities for a fee (such as, for example, the Odum Institute used by the *American Journal of Political Science*, or CASCaD, see Pérignon et al., 2019).
- The fact that more than 700 reviewers participated in this project indicates that there is sufficient expertise in the community to integrate the code and data review into the peer review cycle of a manuscript, with low direct costs. E.g., in a last minor revision round, one reviewer could be assigned by the Department or Associate Editor to review the replication materials and certify reproducibility. However, while the willingness to participate in this project may have been driven by its novelty, one might have to consider other incentives for reviewers when establishing such reproducibility assessments as a regular procedure.

The scope of Code and Data policies extends beyond just enabling computational reproduction; their broader aim is to facilitate the replication of research results in order to assert their robustness and generalizability. Reproducibility does not imply replicability. There may be instances where a study is reproducible but not replicable (e.g., the results can be obtained with the same dataset but not with a new dataset generated in a different context). Conversely, a study might not be reproducible but replicable (e.g., the original dataset may be unavailable so the code cannot be applied, but results with data collected from a different source show the same effects).

We contend, however, that reproducibility serves as a vital foundation for evaluating replicability. A reproducible study boosts confidence in its results, making it meaningful to further examine its robustness and generalizability. The provision of datasets allows for the detection of anomalies and fraud. Materials provided for the reproduction of a study often facilitate its replication as well, by allowing researchers to better understand the structure of data and to apply the same analysis code to new datasets. In addition, in order to support replication studies, materials required to be provided under most code and data policies extend beyond those purely needed for reproduction. Even if datasets are not available and reproducibility thus not achievable, the packages nevertheless contain detailed descriptions of data provenance and variable dictionaries, aiding replication researchers in gathering new data. For surveys, materials include complete questionnaires or their software implementations, while for experimental studies, they encompass experiment instructions, software code, and other resources critical for running a replication study.

In conclusion, our study illuminates the critical importance of reproducibility in maintaining the integrity and credibility of scientific research in Management Science and related fields. By addressing data availability challenges and refining journal code and data review procedures, the academic community can work collaboratively to improve reproducibility. These efforts are essential to ensuring that robust research findings continue to guide decision-making and contribute to the advancement of knowledge.

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ONLINE APPENDIX

A THE MANAGEMENT SCIENCE REPRODUCIBILITY COLLABORATION

The following co-authors lent their time and expertise as reproducibility reviewers to the Management Science Reproducibility project and are credited as “Management Science Reproducibility Collaboration” in the author string.

Diya Abraham, University of Reading
Gabrielle S. Adams, University of Virginia
Arzi Adbi, National University of Singapore, Business School
Jawad M. Addoum, Cornell University
Maja Adena, WZB Berlin
Laxminarayana Yashaswy Akella, Indian Institute of Management Ahmedabad
Pat Akey, University of Toronto
Olivier Akmansoy, HEC Paris; CNRS
Andres Alban, Harvard University, Harvard Medical School
Vitali Alexeev, University of Technology Sydney
Azizjon Alimov, IESEG School of Management
Argun Aman, University of Mannheim
Ali Aouad, London Business School
Gil Appel, George Washington University, School of Business
Nick Arnosti, University of Minnesota
Kashish Arora, Indian School of Business
Thibaut Arpinon, Georg-August Universität Göttingen
Florian M. Artinger, Max Planck Institute for Human Development; Simply Rational - The Decision Institute; Berlin International University of Applied Sciences
Joachim Arts, University of Luxembourg
Lennart Baardman, University of Michigan, Ross School of Business
Zakaria Babutsidze, SKEMA Business School
Golnaz Bahrani, Pennsylvania State University
Somnath Banerjee, North Dakota State University
Chenzhang Bao, Oklahoma State University
Te Bao, Nanyang Technological University, School of Social Science
Opher Baron, University of Toronto, Rotman School of Management
Xabier Barriola, INSEAD
Pedro Monteiro e Silva Barroso, Universidade Católica Portuguesa
Ernest Baskin, Saint Joseph’s University
Robert J. Batt, University of Wisconsin-Madison, Wisconsin School of Business
George Batta, Claremont McKenna College
Anahid Bauer, Institut Mines-Télécom Business School, LITEM, Paris Saclay
Konstantin Bauman, Temple University, Fox School of Business
William Bazley, University of Kansas
Michael Becker-Peth, Erasmus University, Rotterdam School of Management
Mehmet Begen, Western University, Ivey Business School
Nazire Begen, Gebze Technical University
Sylvain Benoit, Université Paris Dauphine - PSL
Loic Berger, University of Lille, IESEG School of Management, LEM - Lille Economie Management; CNRS; iRisk Research Center on Risk and Uncertainty
Noémi Berlin, CNRS, EconomiX, Université Paris Nanterre
Lars Peter Berling, Norwegian University of Science and Technology
Anna Bernard, Catolica Lisbon School of Business and Economics
Jeremy Bertomeu, Washington University in St. Louis
Jędrzej Białkowski, University of Canterbury
Pawel Bilinski, City University of London, Bayes Business School
Jannis Bischof, University of Mannheim
Jeffrey R. Black, University of Memphis
Hayley Blunden, American University
Dion Bongaerts, Erasmus University, Rotterdam School of Management
Felix Bönisch, WZB Berlin
Marieke Bos, Swedish House of Finance
Ciril Bosch-Rosa, Technical University of Berlin
Sylvain Bourjade, TBS Business School
Andrew Boysen, University of North Carolina at Chapel Hill, Kenan-Flagler Business School

Craig Brimhall, University of California Los Angeles, Anderson School of Management

Zuzana Brokesova, University of Economics in Bratislava

J. Paul Brooks, Virginia Commonwealth University

Stephan B. Bruns, Hasselt University

Georgia Buckle, UK Office for National Statistics

Guido Buenstorf, University of Kassel

Gordon Burtch, Boston University

Benjamin Bushong, Michigan State University

Sabrina Buti, Université Paris Dauphine - PSL

Patrick Callery, University of Vermont

Mehmet Canayaz, Pennsylvania State University

Jie Cao, Hong Kong Polytechnic University

Wei Cao, Shanghai University of Finance and Economics

Xinyu Cao, The Chinese University of Hong Kong

Martin Carree, Maastricht University, School of Business and Economics

Vincent Castellani, Pennsylvania State University

Yann Joel Cerasi, Norges Bank

Hannah H. Chang, Singapore Management University

Jin Wook Chang, Korea University Business School

Michelle Chang, Nanyang Technological University

Yanru Chang, City University of New York, Baruch College

Aadhaar Chaturvedi, University of Auckland Business School

Jasmina Chauvin, Georgetown University

Daniel E. Chavez, University of Tennessee

Christopher Chen, Indiana University

Fadong Chen, School of Management & Neuromanagement Lab, Zhejiang University

Josie I Chen, National Taiwan University

Peng-Chu Chen, University of Hong Kong

Roy Chen, RWTH Aachen University

Wei Chen, University of Connecticut

Wei James Chen, National Taiwan University, Department of Agricultural Economics

Yuanyuan Chen, University of Alabama

Zepeng Chen, Hong Kong Polytechnic University

Zhuoqiong Chen, Harbin Institute of Technology, Shenzhen

Lydia Chew, Harvard University, Harvard Business School

Param Pal Singh Chhabra, University of Alberta

Sai Chand Chintala, Cornell University

Ga-Young Choi, City University of London

Seungho Choi, Hanyang University; Queensland University of Technology

Vivek Choudhary, Nanyang Technological University, Nanyang Business School

Vincent Tsz Fai Chow, Hong Kong Polytechnic University, Faculty of Business

Katherine L. Christensen, Indiana University, Kelley School of Business

Doug J. Chung, University of Texas at Austin

Melissa Cinelli, University of Mississippi

Lubomír Cingl, Prague University of Economics and Business

Andre Augusto Cire, University of Toronto, Rotman School of Management

Jeffrey Clark, Stockholm School of Economics

Jeffrey Clement, Augsburg University

John Clithero, University of Oregon

Héloïse Cloléry, Ecole Polytechnique IP Paris, CREST

David R. Clough, University of British Columbia

Nicholas Clyde, Washington University in St. Louis

Andrea Coali, Bocconi University

Irene Comeig, University of Valencia

Nikolai Cook, Wilfrid Laurier University

Joao Correia-da-Silva, University of Porto

Elaine Costa, University of Utah

Alexander Coutts, York University

Ivor Cribben, University of Alberta, Alberta School of Business

Carina Cuculiza, Oklahoma State University

Zimeng (Simon) Cui, University of Utah

Colleen Cunningham, University of Utah, Eccles School of Business

Peter Cziraki, Texas A&M University

Étienne Dagorn, National Institute of Demographic Studies (INED)

Rui Dai, University of Pennsylvania, The Wharton School

Jason Dana, Yale University, Yale School of Management

Nicholas Patrick Danks, Trinity College Dublin, Trinity Business School

Alper Darendeli, Nanyang Technological University

Simon Dato, EBS Universität für Wirtschaft und Recht

Nebojsa Davcik, EM Normandie Business School, Metis Lab

Charles de Grazia, Léonard de Vinci Pôle Universitaire, Research Center

Jose De Sousa, Université Paris Panthéon-Assas

Jelle De Vries, Erasmus University, Rotterdam School of Management

Martijn De Vries, Vrije Universiteit Amsterdam

Oleg Deev, Masaryk University

Ryan DeFronzo, California State University, Fullerton

Lennart Dekker, De Nederlandsche Bank

Arthur Delarue, Georgia Institute of Technology, H. Milton Stewart School of Industrial & Systems Engineering

Elif E. Demiral, Austin Peay State University

Cem Demiroglu, Koc University

Aishwarya Deore, Georgetown University

Andrew Detzel, Baylor University

Azamat Devonaev, University of Luxembourg

Archana Dhinakar Bala, National University of Singapore

Eugen Dimant, University of Pennsylvania

Drew Dimmery, University of Vienna

Stephen G. Dimmock, National University of Singapore

Cheng Ding, Emory University

Likang Ding, University of Alberta

Tingting Ding, James Madison University; Shanghai University of Finance and Economics

Yuheng Ding, University of Maryland

Lu Dong, Southern University of Science and Technology

Karen Donohue, University of Minnesota, Carlson School of Management

Andreas Drichoutis, Agricultural University of Athens

Shaoyin Du, University of North Carolina at Charlotte

Ying Duan, Simon Fraser University

Teodor Duevski, HEC Paris

Huu Nhan Duong, Monash University

Merle Ederhof, University of Zurich, Stanford University

Hussein El Hajj, Santa Clara University, Leavey School of Business

Martin Ellison, University of Oxford

Jonas Nygaard Eriksen, Aarhus University

Miguel Espinosa, Bocconi University

Francesco Fallucchi, University of Bergamo

Xiaohua Fang, Florida Atlantic University

Valeria Fanghella, Grenoble Ecole de Management

Matilde Faralli, Imperial College London

Saleh Farham, University of Alberta

Felix Fattinger, Vienna University of Economics and Business

Stephanie Feiereisen, Montpellier Business School

Yiding Feng, Microsoft Research

Elia Ferracuti, Duke University

Antonio Filippin, University of Milan

Adrien Fillon, University of Cyprus, SINNOPSIS

Stefano Fiorin, Bocconi University

Geoffrey Fisher, Cornell University

Matthew Fisher, Southern Methodist University

Christoph Flath, University of Würzburg

Jens Foerderer, Technical University of Munich

Vincenz Frey, University of Groningen, Department of Sociology

Christoph Fuchs, University of Vienna

Nicolas Fugger, University of Cologne

Sebastian Gabel, Erasmus University Rotterdam, Rotterdam School of Management

Fabian Gaessler, Universitat Pompeu Fabra

Bernhard Ganglmair, University of Mannheim

Manish Gangwar, Indian School of Business

Pedro Angel Garcia Ares, Instituto Tecnológico Autónomo de México

Rajiv Garg, Emory University

José Miguel Gaspar, ESSEC Business School

Chiara Gastaldi, Free University of Bozen-Bolzano

Romain Gauriot, Deakin University

Alan De Genaro, Sao Paulo School of Business Administration (FGV-EAESP)

Yuxin Geng, Tsinghua University

Konstantinos Georgalos, Lancaster University Management School

Diogo Geraldes, University College Dublin, School of Economics; Geary Institute for Public Policy

Leonie Gerhards, King's College London

William Gerken, University of Kentucky

Mike Gibson, University of Maryland, Agricultural and Resource Economics Department

Joren Gijsbrechts, Esade; Ramon Llull University

Sebastian Goerg, Technical University of Munich

Daniel Goetz, University of Toronto, Rotman School of Management

Jim Goldman, University of Warwick

Filip Gonschorek, ZEW Leibniz Centre for European Economic Research

Victor Gonzalez-Jimenez, Erasmus University Rotterdam

Jorgo T.G. Goossens, Radboud University Nijmegen, Institute for Management Research; Tilburg University, Department of Econometrics and Operations Research

Michael Gordy, Federal Reserve Board

Paul M. Gorny, Karlsruhe Institute of Technology
Indranil Goswami, University at Buffalo
Amit Goyal, University of Lausanne
Ruslan Goyenko, McGill University
Tom Grad, Copenhagen Business School
Wesley Greenblatt, Massachusetts Institute of Technology, Sloan School of Management
Martin Gregor, Charles University
Daniela Grieco, University of Milano
Manuel Grieder, UniDistance Suisse; Zurich University of Applied Sciences (ZHAW)
Max R. P. Grossmann, University of Cologne
Sven Grüner, University of Rostock
Sreyaa Guha, Universidade NOVA de Lisboa, Nova School of Business and Economics
Audrey Guo, Santa Clara University
Gang Guo, National University of Singapore
Haihao Guo, Washington University in St. Louis
Lewen Guo, University of Memphis
Dominik Gutt, Erasmus University Rotterdam
André F. Gygax, University of Melbourne
Isaac Hacamo, Indiana University
Simone Haeckl, University of Stavanger
Thomas C. Hagenberg, Northwestern University, Kellogg School of Management
David Hagmann, The Hong Kong University of Science and Technology
Jacob Haislip, Texas Tech University
Eojin Han, Southern Methodist University, Operations Research and Engineering Management
Jiatong Han, Zhejiang University; School of Management & Neuromanagement Lab
Joseph Earle Harvey, Consumer Financial Protection Bureau
Olena Havrylchyk, Université Paris 1 Panthéon-Sorbonne, Centre d'Economie de la Sorbonne
Sonali Hazarika, City University of New York, Baruch College
Leshui He, Bates College
Yuhang He, Nanyang Technological University, Nanyang Business School
William Hedgcock, University of Minnesota
Irina Heimbach, WHU Otto Beisheim School of Management
Brian Henderson, George Washington University
Jurian Hendrikse, Tilburg University
Erin Henry, University of Arkansas
Bradford Hepfer, The University of Iowa
Roberto Hernan, Burgundy School of Business
Holger Herz, University of Fribourg
Anthony Heyes, University of Birmingham
Christian Hildebrand, University of St. Gallen, Institute of Behavioral Science & Technology
Adrian Hillenbrand, Karlsruhe Institute for Technology; Leibniz Centre For European Economic Research
Alexander Hillert, Goethe University Frankfurt; Leibniz Institute for Financial Research SAFE
Michael Hilweg, University of Mannheim
Erik Hjalmarsson, University of Gothenburg
Seth Hoelscher, Missouri State University
Peter Hoffmann, European Central Bank
Brett Hollenbeck, University of California Los Angeles, Anderson School of Management
Niels Holtrop, Maastricht University
Felix Holzmeister, University of Innsbruck, Department of Economics
Swarnodeep Homroy, University of Groningen
Mallick Hossain, Federal Reserve Bank of Philadelphia
Leon Houf, Heidelberg University
Taeya Howell, Brigham Young University, Marriott School of Business
Kejia Hu, University of Oxford
Allen Huang, Hong Kong University of Science and Technology
Jing-Zhi Huang, Pennsylvania State University
Lingbo Huang, Shandong University
Sterling Huang, Singapore Management University
Stefanie J. Huber, University of Bonn
Stanton Hudja, University of Toronto
Jacquelyn Humphrey, University of Queensland
Paul Hünermund, Copenhagen Business School
William Reuben Hurst, University of Michigan, Ross School of Business
Carlos Hurtado, University of Pittsburgh
Kim P. Huynh, Bank of Canada
Kyle Hyndman, University of Texas at Dallas
Armann Ingolfsson, University of Alberta
Panos Ipeiritis, New York University
Ayelet Israeli, Harvard University, Harvard Business School
Alexey Ivashchenko, Vrije Universiteit Amsterdam
Wael Jabr, Pennsylvania State University
Pankaj K. Jain, University of Memphis

Ainhoa Jaramillo-Gutierrez, University Jaume I Castellon

Nahid Javadinarab, University of Luxembourg

Yonghua Ji, University of Alberta

Mofei Jia, Xi'an Jiaotong-Liverpool University

Hansheng Jiang, University of Toronto

Houyuan Jiang, University of Cambridge, Judge Business School

Jiashuo Jiang, Hong Kong University of Science and Technology

Jingdan Tan, Nanyang Technological University

Michal Jirásek, Masaryk University

Brandon Julio, University of Oregon

Heejung (HJ) Jung, Imperial College London, Business School

Daniel Marcel te Kaat, University of Groningen

Jonathan Kalodimos, Oregon State University

Mark Kamstra, York University, Schulich School of Business

Hyo Kang, University of Southern California

Qiang Kang, Florida International University

Salpy Kanimian, Rice University

Martin M. Kapons, University of Amsterdam

Egle Karmaziene, Vrije Universiteit Amsterdam; Swedish House of Finance; Tinbergen Institute

Asad Kausar, American University

Patrick J Kelly, University of Melbourne

Saravanan Kesavan, University of North Carolina at Chapel Hill

Menusch Khadjavi, Vrije Universiteit Amsterdam; Kiel Institute for the World Economy

Hamid Khobzi, University of Sussex

Robizon Khubulashvili, University of San Francisco

Alex G. Kim, University of Chicago

Byungyeon Kim, University of Minnesota

Chungyool Kim, University of Iowa

Dong Soo Kim, Ohio State University

Sehoon Kim, University of Florida

Seojin Kim, Drexel University

Seung Hyun Kim, Yonsei University, School of Business

Soo-hun Kim, Korea Institute of Advanced Science and Technology

Margarita Kirneva, Ecole Polytechnique, CREST; ENSAE Paris

Andrea Kiss, Carnegie Mellon University

Leonardo Mayer Kluppel, Ohio State University

Özgecan Koçak, Emory University

Christoph Kogler, Tilburg University

Christian König-Kersting, University of Innsbruck

Anita Kopányi-Peuker, Radboud University Nijmegen, Institute for Management Research

Lina Koppel, Linköping University

Sharon Koppman, University of California Irvine

Orestis Kopsacheilis, Technical University of Munich

Laura J. Kornish, University of Colorado Boulder, Leeds School of Business

Anne Krahn, Tufts University

Ondřej Krčál, Masaryk University

Srinivasan Krishnamurthy, North Carolina State University

Philipp Kropp, University of Munich

Santanu Kundu, University of Mannheim

Michael Kurschilgen, UniDistance Suisse

David J. Kusterer, Erasmus University Rotterdam, Rotterdam School of Management

Samet Kutuk, Vrije Universiteit Amsterdam

Olga Kuzmina, New Economic School

Ellie Kyung, Babson College

Camille Lacan, CRESEM; IAE School of Management; University of Perpignan Via Domitia

Adrian Lam, University of Pittsburgh

Thomas Lambert, Erasmus University Rotterdam

Lauren Lanahan, University of Oregon

Mike Langen, CPB Netherlands Bureau for Economic Policy Analysis

Nadzeja Laurentsyeva, Ludwig-Maximilians-Universität München

Kelvin K. F. Law, Nanyang Technological University

Quoc Thai Le, University of Trento, Department of Economics and Management

Choonsik Lee, University of Rhode Island

Daniel Lee, University of Delaware

Kyeong Hun Lee, University of Alabama, Culverhouse College of Business

Sunkee Lee, Carnegie Mellon University, Tepper School of Business

Yeonjoo Lee, University of Minnesota, Carlson School of Management

Murray Lei, Queen's University

Zhou Lei, Nanyang Technological University, Nanyang Business School

Stephan Leitner, University of Klagenfurt

Gabriele Mario Lepori, University of Southampton

David E. Levari, Harvard University, Harvard Business School

Ben William Lewis, Brigham Young University

Benjamin T. Leyden, Cornell University

Chenghuai Li, Duke University, Fuqua School of Business

Jiasun Li, George Mason University

King King Li, Shenzhen University, Shenzhen Audencia Financial Technology Institute

Linfeng Li, University of Michigan

Meng Li, University of Houston

Shukai Li, Northwestern University

Shuo Li, Singapore Management University

Ye Li, University of California Riverside

Yushen Li, Jinan University, Institute of Industrial Economics

Chuchu Liang, University of California, Irvine

Stanley Lim, Michigan State University

Mingfeng Lin, Georgia Tech

Po-Hsuan Lin, California Institute of Technology

Yunduan Lin, University of California Berkeley

Sera Linardi, University of Pittsburgh

William Lincoln, Claremont McKenna College

Michaela Lindenmayr, Technical University of Munich

Martina Linnenluecke, University of Technology Sydney

Ariel Listo, University of Maryland

Robin Litjens, Tilburg University

Chengwei Liu, European School of Management and Technology

Dingyue (Kite) Liu, University of California Santa Barbara

Fang Liu, University of the Chinese Academy of Sciences

Haibo Liu, Claremont Colleges, Keck Graduate Institute

Haiyang Liu, Nanyang Technological University

Jiaxin Liu, Morgan State University

Kaiqi Liu, Maastricht University, Department Microeconomics and Public Economics

Nan Liu, Boston College

Sheng Liu, University of Toronto

Xiaojin Liu, Virginia Commonwealth University

Neta Livneh, Tel Aviv University

Tatiana Lluent, European School of Management and Technology

Nils Loehndorf, University of Luxembourg

Matthijs Lof, Aalto University, School of Business

Youenn Loheac, Rennes School of Business

Paul Lohmann, University of Cambridge, Judge Business School

Luis Arturo Lopez, University of Illinois at Chicago

Matej Lorko, University of Economics in Bratislava; Prague University of Economics and Business

Francesca Lotti, Bank of Italy, DG Economics, Statistics and Research

Joy Lu, Carnegie Mellon University

Xinyu Lu, HEC Paris

Jonathan Luffarelli, Montpellier Business School

Wolfgang J. Luhan, University of Portsmouth

Hoang Luong, University of Queensland

Guodong Lyu, Hong Kong University of Science and Technology

Liang Ma, San Diego State University

Leonardo Madio, University of Padova

Kai Maeckle, University of Mannheim

Mahdi Mahmoudzadeh, University of Auckland Business School

Patrick Maillé, IMT Atlantique

Vincent Mak, University of Cambridge, Cambridge Judge Business School

Antoine Malézieux, Burgundy School of Business

Shawn Mankad, North Carolina State University

César Mantilla, Universidad del Rosario

Benny Mantin, University of Luxembourg

Marco Mantovani, Università degli Studi di Milano Bicocca, Dipartimento di Economia

Giacomo Marchesini, Copenhagen Business School

Juri Marcucci, Bank of Italy

Diego Marino Fages, Durham University

Aidas Masiliunas, University of Sheffield

Sébastien Massoni, Université de Lorraine; Université de Strasbourg; CNRS; BETA

Nunez Matias, Ecole Polytechnique, CREST; CNRS

Thomas Matthys, University of Technology Sydney

Martin Mattsson, National University of Singapore

Thomas Andreas Maurer, University of Hong Kong

Patrick Maus, University of Nottingham

Merve Mavuş Kütük, University of Amsterdam

Malte M. Max, Vrije Universiteit Amsterdam

Christoph Meinerding, Deutsche Bundesbank

Matt Meister, University of Colorado Boulder; University of San Francisco

Dong Meitong, University of Hong Kong

Eduardo Melero, Universidad Carlos III de Madrid

Diogo Mendes, Stockholm School of Economics

Tyler Menzer, University of Iowa

Christoph Merkle, Aarhus University

Jason Merrick, Virginia Commonwealth University
Steffen Meyer, Aarhus University; Danish Finance Institute
Tomáš Miklánek, Prague University of Economics and Business
Wladislaw Mill, University of Mannheim
Stefan Minner, Technical University of Munich
Emil Mirzayev, University College London, School of Management
Sergio Mittlaender, Fundação Getulio Vargas Law School in São Paulo; Max Planck Institute for Social Law and Social Policy
Stig Vinther Møller, Aarhus University
Andras Molnar, University of Michigan, Department of Psychology
David Moore, Loyola Marymount University
Sandra Mortal, University of Alabama
Giovanni Moscariello, Stockholm School of Economics
Yuting Mou, Southeast University
Jifeng Mu, Alabama A&M University
Clemens Mueller, University of Mannheim
Anirban Mukherjee, Cornell University; INSEAD
Sara Mustafazade, University of Montpellier
Kumar Muthuraman, University of Texas-Austin
Alper Nakkas, University of Texas at Arlington
Jim Naughton, University of Virginia
Hunter Boon Hian Ng, City University of New York, Baruch College
Lily Nguyen, University of Queensland
Mike Nguyen, University of Southern California
Ngoc Phuong Anh Nguyen, University of Technology Sydney
Thi Thuy Tien Nguyen, University of Auckland
Amy Nguyen-Chyung, University of California San Diego, Rady School of Management
Nicos Nicolaou, University of Warwick
Sven Nolte, Radboud University Nijmegen
Arjan Non, Erasmus University Rotterdam
Bernt Arne Ødegaard, University of Stavanger
Yuval Ofek-Shanny, Friedrich-Alexander-Universität Erlangen-Nürnberg
Chang Hoon Oh, University of Kansas
Christopher Yves Olivola, Carnegie Mellon University
Thomas C. Omer, University of Nebraska-Lincoln
Andreas Orland, Corvinus University of Budapest
Tizian Otto, Yale University; University of Hamburg
Manlu Ouyang, New York University, Stern School of Business
Hakan Ozyilmaz, Toulouse School of Economics
Nicholas A. Pairolo, United States Patent and Trademark Office
Stefan Palan, University of Graz
Navya Pandit, University of Cologne
Dominik Papies, University of Tuebingen, School of Business and Economics
Jiyong Park, University of North Carolina at Greensboro
Tae-Youn Park, Sungkyunkwan University
Chris Parker, American University
Vinay Patel, University of Technology Sydney
Grzegorz Pawlina, Lancaster University
Elise Payzan-Le Nestour, University of New South Wales
Graeme Pearce, Bangor University
Thomas Peeters, Erasmus University Rotterdam, Erasmus School of Economics; Tinbergen Institute; Erasmus Research Institute in Management
Jana Peliova, University of Economics in Bratislava
Zhuozhen Peng, Central University of Finance and Economics
Christophe Pérignon, HEC Paris
Noemi Peter, University of Groningen
Christian Peukert, University of Lausanne, Faculty of Business and Economics (HEC)
Hieu Phan, University of Massachusetts Lowell
Aviva Philipp-Muller, Simon Fraser University
Kenny Phua, University of Technology Sydney
Matthew Pierson, University of Pennsylvania, The Wharton School
Tomáš Plíhal, Masaryk University
Matteo Ploner, University of Trento, Department of Economics and Management
Simon Porcher, Université Paris Panthéon-Assas
Matthieu Pourieux, Rennes School of Business; Univ Rennes, CNRS, CREM-UMR6211
Susanne Preuss, University of Amsterdam
Jakub Procházka, Masaryk University, Faculty of Economics and Administration
Shaolin Pu, University of Kansas, School of Business
Žiga Puklavac, Tilburg University
Hanzhang Qin, Amazon; National University of Singapore
Tian Qiu, University of Alabama
Xincheng Qiu, University of Pennsylvania

Rima-Maria Rahal, Max Planck Institute for Research on Collective Goods

Amin Rahimian, University of Pittsburgh

Mohammadreza Rajabzadeh, York University, Schulich School of Business

Oliver Randall, University of Melbourne

Soumya Ray, National Tsing Hua University, Institute of Service Science

Oliver Rehbein, Vienna University of Economics and Business

Jurij-Andrei Reichenecker, University of Strathclyde

Nicholas Reinholtz, University of Colorado Boulder

J. Philipp Reiss, Karlsruhe Institute of Technology

Jean-Paul Renne, University of Lausanne

Sadat Reza, Nanyang Technological University

Paul Richardson, Pennsylvania State University

Steven Riddiough, University of Toronto

Marc Oliver Rieger, University of Trier; University of Economics Ho Chi Minh City

Cesare Righi, Universitat Pompeu Fabra, Department of Economics and Business; UPF Barcelona School of Management; Barcelona School of Economics

Rainer Michael Rilke, WHU Otto Beisheim School of Management

Julio Riutort, Universidad Adolfo Ibáñez

Cesare Robotti, University of Warwick

Nathalie Römer, Leibniz University Hannover

Paul Romser, Ludwig-Maximilians-Universität München

Julia Rose, Erasmus University Rotterdam, Erasmus School of Economics; Tinbergen Institute

Michael Rose, Max Planck Institute for Innovation and Competition

Federico Rossi, Purdue University

Borzou Rostami, University of Alberta

Kasper Roszbach, Norges Bank; University of Groningen

Kristian Rotaru, Monash University, Monash Business School

Yefim Roth, University of Haifa

Daniele Rotolo, University of Sussex; Technical University of Bari

Christina Rott, Vrije Universiteit Amsterdam; Tinbergen Institute

Bryan Routledge, Carnegie Mellon University

Brian Rubineau, McGill University

Hannes Rusch, Maastricht University

Ilya O. Ryzhov, University of Maryland

Pedro Saffi, University of Cambridge, Judge Business School

Mehmet Saglam, University of Cincinnati

Margaret Samahita, University College Dublin

Panagiotis Sarantopoulos, Athens University of Economics and Business; University of Manchester

Vahid Sarhangian, University of Toronto

Secil Savaseneril, Middle East Technical University, Industrial Engineering Department

Harald Scheule, University of Technology Sydney

Maximilian Schleritzko, Vienna Graduate School of Finance

Max Schmidman, University of Virginia

Daniela Stephanie Schoch, emlyon business school

Marina Schröder, Leibniz University Hannover

Erik Christian Montes Schütte, Aarhus University; Danish Finance Institute

Daniel Schwartz, University of Chile

Frederik Schwerter, Frankfurt School of Finance and Management

Robert Seamans, New York University

Matthias Seifert, IE University, IE Business School

Tom Servranckx, Ghent University, Faculty of Economics and Business Administrations

Nagaraajan Sethuraman, University of Kansas

Victoria Sevchenko, INSEAD

Divyesh Rajendra Shah, University of Toronto

Rachna Shah, University of Minnesota

Kartikey Sharma, Zuse Institute Berlin

Padma Sharma, Federal Reserve Bank of Kansas City

Amy Sheneman, Ohio State University

Yunting Shi, Shanghai Jiao Tong University, Antai College of Economics and Management

Ling Shuai, Tianjin University

Simon Siegenthaler, University of Texas at Dallas

John Silberholz, University of Michigan

Rui Silva, University of East Anglia

Katherine Silz-Carson, U.S. Air Force Academy

Felipe Simon, University of Minnesota

Raghav Singal, Dartmouth College, Tuck School of Business

Nitish Ranjan Sinha, Board of Governors of the Federal Reserve System

Spyros Skouras, Athens University of Economics and Business

David Smerdon, University of Queensland

Katrin Smolka, University of Warwick, Warwick Business School

Adriaan Soetevent, University of Groningen

Elvira Sojli, University of New South Wales

Konstantin Sokolov, University of Memphis

Jeeva Somasundaram, IE Business School

Yoonseock Son, University of Notre Dame

Ju Myung Song, University of Massachusetts Lowell

Vikas Soni, University of South Florida

Doron Sonsino, University of Limassol, Cyprus

Matthew Souther, University of South Carolina

Christophe Spaenjers, University of Colorado Boulder

Martin Spann, Ludwig-Maximilians-Universität München, LMU Munich School of Management

Eirini Spiliotopoulou, Tilburg University

Jeffrey Starck, University of Cologne

Austin Starkweather, University of South Carolina

Dayton Steele, University of Minnesota, Carlson School of Management

Matthias Stefan, University of Innsbruck

Frauke Stehr, Maastricht University

Eva Steiner, Pennsylvania State University

Lucas Stich, Julius-Maximilians-Universität Würzburg

Thomas Stoeckl, MCI The Entrepreneurial School

Jan Stoop, Erasmus University Rotterdam, Erasmus School of Economics

Karoline Ströhlein, University of Regensburg

Robert Stüber, New York University Abu Dhabi

Jason Sturgess, Queen Mary University of London

Yuhan Su, Tianjin University

Yuxin Su, SKEMA Business School

Rémi Suchon, Université Catholique de Lille

Mengtian Sui, City University of New York, Baruch College

Sandra Sülz, Erasmus University Rotterdam, Erasmus School of Health Policy & Management

Elie Sung, HEC Paris

Marta Szymanowska, Erasmus University, Rotterdam School of Management

Giovanni Alberto Tabacco, Freelance researcher

David Tannenbaum, University of Utah

Necati Tereyagolu, University of South Carolina, Darla Moore School of Business

Chloe Tergiman, Pennsylvania State University

Marco Testoni, Miami Herbert Business School, University of Miami

Richard Thakor, University of Minnesota; Massachusetts Institute of Technology, Laboratory for Financial Engineering

Wing Wah Tham, University of New South Wales

Samuel Thelaus, London School of Economics

Simon Thielen, MCI The Entrepreneurial School

Lu Tong, Southwestern University of Finance and Economics

Ozlem Tonguc, Binghamton University

Mirco Tonin, Free University of Bozen-Bolzano

Sinem Yagmur Toraman, Johns Hopkins University, Department of Economics

Marco Tortoriello, Bocconi University

J. Dustin Tracy, Augusta University

James Tremewan, IESEG School of Management

Muktak K. Tripathi, Temple University

Gunseli Tumer-Alkan, Vrije Universiteit Amsterdam

Danko Turcic, University of California Riverside

Theodore Turocy, University of East Anglia

Hanu Tyagi, University of Minnesota

Maximiliano Udenio, KU Leuven

Sezer Ulku, Georgetown University, McDonough School of Business

Michael Ungeheuer, Aalto University

Steven Utke, University of Connecticut

Cihan Uzmanoglu, SUNY, Binghamton University

Matteo Vacca, Aalto University, School of Business

Philip Valta, University of Bern

Michel Van Der Borgh, Copenhagen Business School

Jesse Van Der Geest, Tilburg University

Milan Van Steenvoort, Maastricht University

Roel Van Veldhuizen, Lund University

Prasad Vana, Dartmouth College, Tuck School of Business

Mario Vanhoucke, Ghent University; Vlerick Business School; University College London

Bart Vanneste, University College London

Joseph Vecchi, Gothenburg University

Sriram Venkataraman, University of South Carolina, Darla Moore School of Business

Marcella Veronesi, Technical University of Denmark; University of Verona

Sergio Vicente, University of Luxembourg

Sebastian Villa, University of New Mexico

Marta Villamor Martin, University of Maryland

Lynne Vincent, Syracuse University

Theodor Vladasel, Universitat Pompeu Fabra, Barcelona
School of Economics

Stefan Voigt, University of Copenhagen

Joachim Vosgerau, Bocconi University

Christian A. Vossler, University of Tennessee

Angela Vossmeier, Claremont McKenna College

Hannes F. Wagner, Bocconi University

David M. Waguespack, University of Maryland

Edward Walker, University of California Los Angeles

Matthew Walker, Newcastle University

Markus Walzl, University of Innsbruck

Zhixi Wan, University of Hong Kong

Charles C.Y. Wang, Harvard University, Harvard
Business School

Joseph Tao-Yi Wang, National Taiwan University,
Department of Economics

Kanix Wang, University of Cincinnati

Victor Xiaoqi Wang, California State University Long
Beach

Xiaohong Wang, University of Pittsburgh

Yiwei Wang, Zhejiang University

Xavier S. Warnes, Stanford University

Lilia Wasserka-Zhurakhovska, University of Duisburg-
Essen

Wei Wei, University of Oklahoma

Stefan Weiergraeber, Indiana University, Department of
Economics

Patrick Weiss, Reykjavik University

Jingjing Weng, Temple University

Wei-Chien Weng, National Taiwan University

James Weston, Rice University

Joshua Tyler White, Vanderbilt University

Matthias Wibral, Maastricht University

Jared Williams, University of South Florida

Ole Wilms, Hamburg University; Tilburg University

Franz Wirl, University of Vienna

Adrian Wolanski, University of California San Diego,
Department of Economics

M.H. Franco Wong, University of Toronto

Daniel John Woods, University of Innsbruck

Biyu Wu, University of Nebraska-Lincoln

Yiran Wu, Vrije Universiteit Amsterdam

Ziye Wu, National University of Singapore

David Wuttke, Technical University of Munich, TUM
School of Management, TUM Campus Heilbronn

Yuze Xia, Northwestern University, Kellogg School of
Management

Jingui Xie, Technical University of Munich

Wen Xie, City University of New York, Baruch College

Feiyu Xu, Hong Kong University of Science and
Technology

Luze Xu, University of California Davis

Sikun Xu, Washington University in St. Louis

Simon Xu, Harvard University, Harvard Business School

Yilong Xu, Utrecht University School of Economics,
Utrecht University

Rui Xue, La Trobe University

Beril Yalcinkaya, University of Maryland

Ruijing Yang, Chinese University of Hong Kong

Yadi Yang, Nanjing Audit University

Huang Yao, Central South University, Business School;
Hunan Agricultural University, College of Economics

Shiqing Yao, Monash University

Yaojun Ke, Nanyang Technological University

Ozge Yapar, Indiana University, Kelley School of Business

Eduard Yelagin, University of Memphis

Ira Yeung, University of British Columbia

Erdem Dogukan Yilmaz, Erasmus University
Rotterdam

Levent Yilmaz, Turkish-German University

Woongsun Yoo, Central Michigan University

Simon (Seongbin) Yoon, University of California Irvine

Sora Youn, Texas A&M University

Alex Young, Hofstra University

Jin Yu, Monash University

Jungju Yu, Korea Advanced Institute of Science and
Technology

Junhao Vincent Yu, Miami University, Farmer School of
Business

Lizi Yu, University of Queensland

Huaiping Yuan, The Chinese University of Hong Kong-
Shenzhen, SME and SFI

Yuan Yuan, Purdue University

Lei Yue, University of California Santa Barbara

Anita Zednik, Vienna University of Economics and
Business

Yasser Zeinali, University of Alberta

Shenghui Zhai, University of the Chinese Academy of
Sciences

Xintong Zhan, Fudan University

Aiqi Zhang, Wilfrid Laurier University, Lazaridis School
of Business and Economics

Chengyu Zhang, McGill University

Huanan Zhang, University of Colorado Boulder

Huanren Zhang, University of Southern Denmark
Hulai Zhang, Tilburg University; ESCP Business School
Jack H. Zhang, Nanyang Technological University
Le (Lyla) Zhang, Macquarie University
Quan Zhang, Nanyang Technological University
Renyu Zhang, Chinese University of Hong Kong
Ruishen Zhang, Shanghai University of Finance and
Economics
Shu Zhang, Shanghai University of Finance and
Economics
Sili Zhang, Ludwig-Maximilians-Universität München
Walter W. Zhang, University of Chicago, Booth School
of Business
Zhiqi Zhang, Washington University in St. Louis, Olin
Business School
Jiayu (Kamessi) Zhao, Massachusetts Institute of
Technology, Operations Research Center
Xiaofei Zhao, Georgetown University
Zhongyu Zhao, University of Hong Kong
Jiakun Zheng, Renmin University of China, School of
Finance
Yaping Zheng, McGill University
Zhanzhi Zheng, University of North Carolina at Chapel
Hill, Kenan–Flagler Business School
Aner Zhou, San Diego State University
Hongyi Zhu, University of Texas at San Antonio
Jason Zhu, Microsoft
Yayongrong Zhu, University of Queensland
Christian Zihlmann, University of Fribourg, Berne
Business School
Marius Zoican, University of Toronto
Ro'i Zultan, Ben-Gurion University of the Negev
Zhuan Zuo, University of the Chinese Academy of
Sciences

B ADDITIONAL TABLES AND FIGURES

TABLE B.1: SOFTWARE USED IN ARTICLES
WITH AND WITHOUT REPORT

	Has Report ($N = 459$)	No Report ($N = 30$)
Stata	60.1%	43.3%
R	19.2%	23.3%
Matlab	17.9%	26.6%
SAS	12.9%	13.3%
Python	10.7%	13.3%
Mathematica	1.7%	6.7%
SPSS	1.3%	0.0%
Other	5.7%	13.3%

TABLE B.2: REASONS FOR NON-REPRODUCIBILITY FOR ARTICLES
WITH REPLICATION PACKAGE, BY POLICY

	Before 2019 policy ($N = 18$)	Since 2019 policy ($N = 136$)
No access to dataset.	61.1%	88.2%
Issues with software/hardware requirements.	5.6%	2.9%
Code or parts of code/functions missing.	55.6%	12.5%
Insufficient documentation, missing information.	11.1%	7.4%
Unresolvable errors when executing code.	11.1%	5.1%
Reproduction yields (partly) different results.	11.1%	4.4%

TABLE B.3: DISTRIBUTION OF ARTICLE TYPES/METHODS
FOR EACH JOURNAL DEPARTMENT, SINCE 2019 POLICY

		Theory				
		Lab/online experiment	/Simulation /Computation	Survey study	Field experiment	Empirical data
SMS	($N = 5$)	0	100	0	0	0%
BDE	($N = 66$)	70	3	5	8	15%
ENI	($N = 10$)	10	0	0	0	90%
RMA	($N = 19$)	0	84	0	0	16%
ACC	($N = 57$)	7	0	2	0	91%
OPM	($N = 38$)	11	32	5	11	42%
OPT	($N = 6$)	0	100	0	0	0%
BDA	($N = 14$)	0	100	0	0	0%
FIN	($N = 124$)	5	15	1	1	78%
HCM	($N = 16$)	0	19	0	0	81%
INS	($N = 19$)	0	11	5	11	74%
MKG	($N = 20$)	10	5	0	15	70%
ORG	($N = 13$)	0	8	8	0	85%
BST	($N = 12$)	0	8	8	25	58%
Total	($N = 419$)	15	20	2	4	59%

Note: Department acronyms are SMS: Stochastic Models and Simulations, BDE: Behavioral Economics and Decision Analysis, ENI: Entrepreneurship and Innovation, RMA: Revenue Management and Market Analytics, ACC: Accounting, OPM: Operations Management, OPT: Optimization, BDA: Big Data Analytics/Data Science, FIN: Finance, HCM: Healthcare Management, INS: Information Systems, MKG: Marketing, ORG: Organizations, BST: Business Strategy.

C ROBUSTNESS ANALYSES

In Tables C.1 and C.2 we replicate our main results reported in Section III (Figure 1 and Table 4) based on different samples from the set of all submitted reports. In Table C.1, as a “lower” bound we report the distribution of overall assessments when using the lower assessment whenever we have obtained two reports for an article. As a randomized approach (“rand.”), we report the distribution of assessments which we obtain when simulating 10,000 replications of the dataset, in each of which one report is randomly selected when multiple reports are available. The “upper” bound is represented by the case where we select the higher assessment whenever we have two reports for an article (as reported in Figure 1).

The first three result columns in Table C.1 only consider reports for verifiable articles (i.e., where data was available if needed, and soft- and hardware requirements were met) that were subject to the 2019 disclosure policy. The second set of three columns also includes reports for non-verifiable articles, and the third set focuses on reports on articles that were accepted before the disclosure policy was introduced and voluntarily provided replication materials.

Differences between the three approaches to aggregating multiple reports (lower bound, randomized, upper bound) are in the expected direction but small in size. Compared to taking the higher overall assessment with a share of fully or largely reproduced articles of 95.3% for verifiable articles, this number is 91.4% when taking the lower assessment, and 93.8% when randomizing which of two assessments is considered. Similarly, the numbers for all assessed articles and articles from before the 2019 policy change do not vary much.

The regressions reported in Table C.2, assessing the disclosure policy effect at the report level while clustering standard errors at the article level to account for multiple reports per article, replicate our results at the article level (reported in Table 4 in the main text).

TABLE C.1: ROBUSTNESS CHECKS ON OVERALL ARTICLE REPRODUCIBILITY ASSESSMENTS

	Since 2019 policy, verifiable articles ($N = 297$)			Since 2019 policy, all assessed articles ($N = 419$)			Before 2019 policy, all assessed articles ($N = 40$)		
	lower	rand.	upper	lower	rand.	upper	lower	rand.	upper
Not verifiable				29.4%	26.7%	23.9%	15.0%	12.5%	10.0%
Largely not verifiable				6.4%	6.0%	5.3%	17.5%	17.5%	17.5%
Not reproduced	4.5%	3.0%	2.0%	2.9%	2.0%	1.4%	10.0%	10.0%	10.0%
Largely not reproduced, with major issues	4.1%	3.2%	2.7%	2.6%	2.2%	1.9%	10.0%	8.8%	7.5%
Largely reproduced, with minor issues	68.4%	60.1%	52.2%	43.9%	40.5%	37.0%	37.5%	35.0%	32.5%
Fully reproduced	23.0%	33.7%	43.1%	14.8%	22.7%	30.5%	10.0%	16.2%	22.5%
Fully or largely reproduced	91.4%	93.8%	95.3%	58.7%	63.2%	67.5%	47.5%	51.2%	55.0%

Note: The percentage values in columns “lower” (“upper”) are the result of only considering the more negative (positive) report in case there are two reports for the same article. The “upper” columns thus correspond to the results in Figure 1 in the main text. The values in columns “rand.” are the result of 10,000 replications in each of which one report was randomly selected when there are two reports for the same article.

TABLE C.2: REGRESSING REPRODUCIBILITY ON DISCLOSURE POLICY EXISTENCE, REPORT LEVEL

Model	(1)		(2)		(3)	
Sample of articles	All incl. no package		All with package		All verifiable	
	Coeff	StdErr	Coeff	StdErr	Coeff	StdErr
Constant	0.098***	(0.020)	0.547***	(0.077)	0.778***	(0.069)
Policy	0.526***	(0.031)	0.077	(0.081)	0.159**	(0.070)
Report observations	1,045		753		504	
R^2	0.251		0.002		0.029	

Note: The dependent variable is a binary indicator whether the article was classified as “fully reproduced” or “largely reproduced”, or not. Standard errors are clustered at the article level. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

In addition to an overall assessment, we asked our reviewers to provide individual assessments for each table and figure in the article that are based on code and/or data analysis, and a summary assessment of other analyses reported in the manuscript (that is, how many of those results they could reproduce). Many reviewers did so, but not all. Some articles only included figures and/or tables that were not based on code or data analysis. As a result, the sample size in terms of articles is slightly lower for this analysis.

Table C.3 shows that, as to be expected, overall assessments and individual assessments are highly correlated. If an article was overall classified as “Fully reproduced,” then more than 99% of tables and figures and more than 92% of other results could be reproduced. If an article was overall classified as “Not reproduced,” the shares of reproduced tables, figures, and other results are 3%, 8%, and 25%, respectively.

TABLE C.3: SHARE OF TABLES, FIGURES, AND OTHER RESULTS ASSESSED AS AT LEAST LARGELY REPRODUCIBLE, BY OVERALL REPRODUCIBILITY ASSESSMENT, SINCE 2019 POLICY

	Tables ($N = 374$)	Figures ($N = 301$)	Other Results ($N = 145$)
Fully reproduced	99.1 %	99.7 %	92.3 %
Largely reproduced, with minor issues	86.6 %	84.9 %	63.4 %
Largely not reproduced, with major issues	12.0 %	30.5 %	0.0 %
Not reproduced	2.7 %	7.5 %	23.7 %

Figures C.1, C.2, and C.3 show the distribution of assessment outcomes for tables, figures, and other results, respectively, for different samples. The first panel of each figure displays the distributions over all tables, all figures, and all other results, respectively. To account for the fact that articles differ substantially in the number of included tables and figures, for the second panel of each figure we first calculate the distribution of assessment outcomes for each article (using the report with the higher overall assessment, as above), and then average over all articles. In the third panel, we only consider articles which have been deemed verifiable (i.e., for which the dataset was available to the reviewer and soft- and hardware requirements could be met).

We find that it makes little difference how we aggregate individual results, in particular for tables and figures. The share of at least largely reproduced tables is 58-62% (depending on the aggregation method) for all articles, and 88% when considering verifiable articles only. For figures, these shares are 68-70% for all articles and 90% for verifiable articles. For other results we only distinguish between reproducible and not reproducible and results are based on a smaller sample (not all articles report other results, and not all reviewers assessed other results). The respective numbers here are 66-83% for all articles and 75% for verifiable articles.

FIGURE C.1: REPRODUCIBILITY ASSESSMENTS OF TABLES, SINCE 2019 POLICY

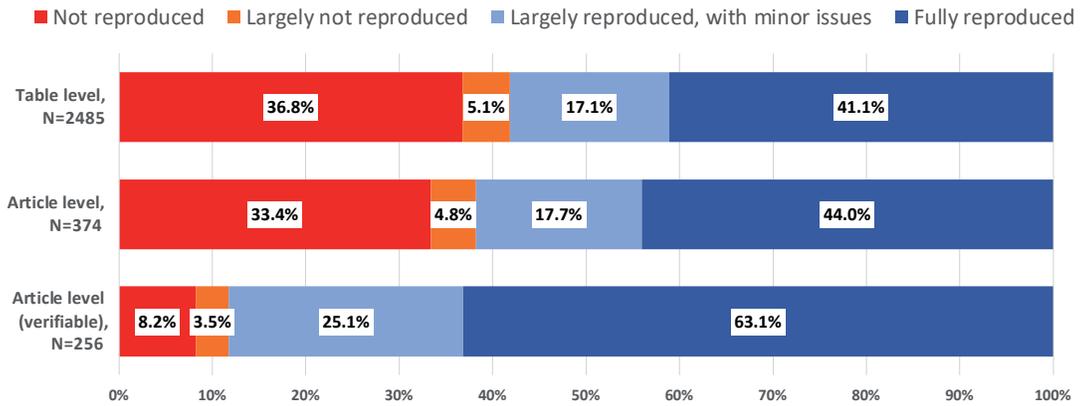


FIGURE C.2: REPRODUCIBILITY ASSESSMENTS OF FIGURES, SINCE 2019 POLICY

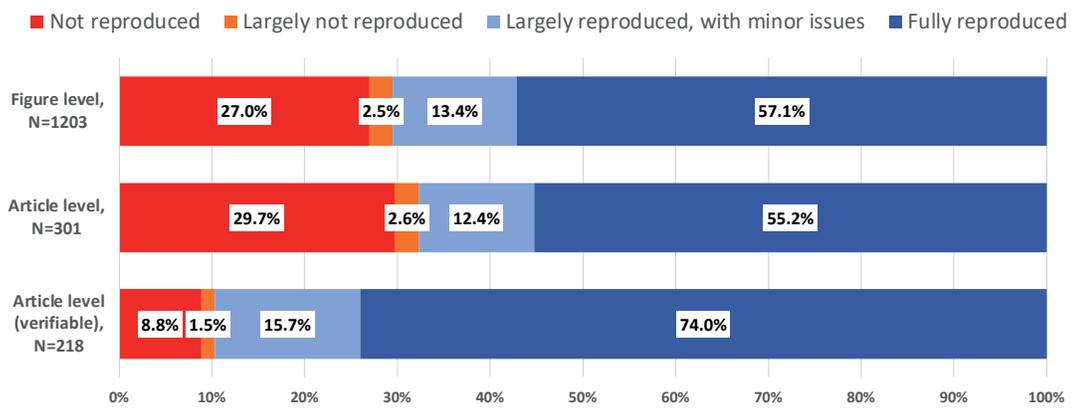
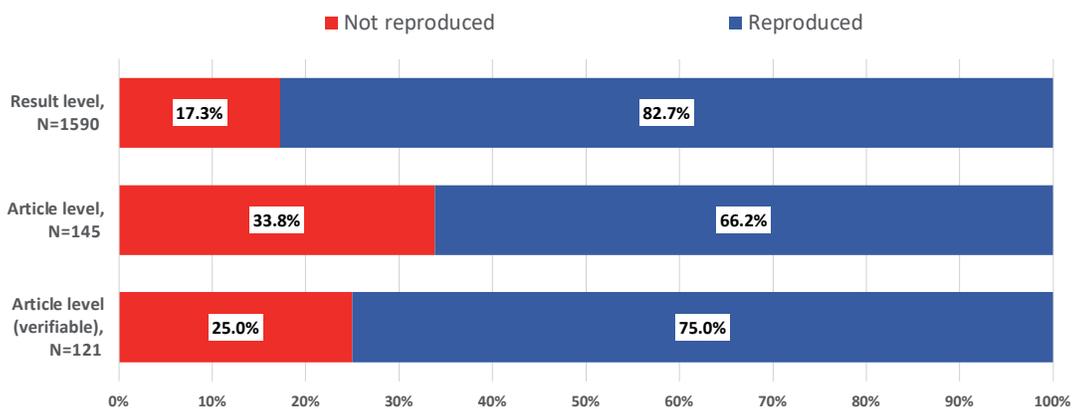


FIGURE C.3: REPRODUCIBILITY ASSESSMENTS OF OTHER RESULTS, SINCE 2019 POLICY



D REVIEWER CONSISTENCY

For articles for which we were able to obtain two reviews, Table D.1 displays the assessments of the reviewer with the higher assessment and the second reviewer (with the same or lower assessment). Among the 120 reviewer pairs with different assessments, the reviewer with the lower assessment of reproducibility rated the straightforwardness of the reproduction lower (avg. of 71.7 vs. 80.9 on a scale 0-100, $p < 0.001$), was (weakly significantly) less likely to rate the readme file as sufficient ($p = 0.063$), and rated their own methodological expertise as lower (avg. of 80.9 vs. 84.8 on a scale 0-100, $p < 0.001$). No differences between reviewers with lower and higher rating were found with respect to time spent on the review (9.2 vs. 10.4 hours, $p = 0.478$), and for their self-assessed expertise in the topic of the article ($p = 0.842$).

TABLE D.1: REVIEWER CONSISTENCY

Reviewer with (weakly) lower assessment	Reviewer with (weakly) higher assessment			
	Fully	Largely	Largely not	Not
Fully reproduced.	31			
Largely reproduced, with minor issues.	64	65		
Largely not reproduced, with major issues.	5	20	8	
Not reproduced.	2	13	16	70

E PROJECT DOCUMENTATION

E.1 Reviewer Invitation Emails

Invitation email to *Management Science* reviewers

Dear First Name,

As you may know, recently *Management Science* initiated the *Management Science Reproducibility Project (ManSciReP)*. In this project, we assess the computational reproducibility of studies published in the journal. Since 2020, the Code & Data Editor verifies that replication materials are provided but does not attempt reproduction itself. In this project, we aim to quantify the reproducibility of results published in *Management Science* articles before and after the new Data and Code Disclosure Policy came into effect.

I am writing to see if you would be willing to review a replication package of a paper recently accepted for publication in *Management Science*. You are receiving this email because you have served as a reviewer for *Management Science* before.

If you are willing to review, we would assign you a paper from your own field of research, and using software that you are familiar with. We would then ask you to report back within 4-6 weeks to what extent you were able to reproduce the paper's main results, and what the obstacles were.

This call for reviewers is open to any researcher in the community, including advanced Ph.D. students. Please feel free to forward this call to colleagues and students.

All participating reviewers who submit a report will become members of a "consortium co-authorship" for the final publication that reports the outcomes of the project. This consortium, the "Management Science Reproducibility Collaboration," will be listed as a co-author on the front page of the article, with all members listed by name and affiliation in the paper's appendix.

If you are willing to participate as a reviewer, we ask you to complete this short survey (before January 15, 2023), so we can match you with a paper from your field.

[Begin Survey](#)

In case of any questions, please contact the project team at ManSciReP@informs.org.

Sincerely,

David Simchi-Levi

Editor-in-Chief, *Management Science*

Invitation email to others

Dear Researcher:

We would like to draw your attention to an opportunity to join a new project on the reproducibility of studies published in Management Science as a reviewer.

In the Management Science Reproducibility Project (ManSciReP), we assess the computational reproducibility of studies published in the journal. Since 2020 the Code & Data Editor verifies that replication materials are provided but does not attempt reproduction itself. In this project, we aim to quantify the reproducibility of results published in Management Science articles before and after the new Data and Code Disclosure Policy came into effect.

If you would be willing to review, we would assign you a paper from your own field of research, and using software that you are familiar with. We would then ask you to report back within 4-6 weeks to what extent you were able to reproduce the paper's main results, and what the obstacles were.

This call for reviewers is open to any researcher in the community, including advanced PhD students. Please feel free to forward this call to colleagues and students.

All participating reviewers who submit a report will become members of a "consortium co-authorship" for the final publication that reports the outcomes of the project. This consortium, the "Management Science Reproducibility Collaboration", will be listed as a co-author on the front page of the article, with all members listed by name and affiliation in the paper's appendix.

If you are willing to participate as a reviewer, we ask you to complete this short survey, so we can match you with a paper from your field.

[Survey link](#)

In case of any questions, please contact the project team at ManSciReP@informs.org.

Sincerely,

David Simchi-Levi
Editor-in-Chief, Management Science

Miloš Fišar, Ben Greiner, Christoph Huber, Elena Katok, and Ali Ozkes
Project coordinators

E.2 Reviewer registration survey

Management Science Reproducibility Project

Reviewer registration form

The Management Science Reproducibility Project (ManSciReP) assesses the computational reproducibility of studies published in the journal.

If you are willing to participate as a reviewer, we kindly ask you to complete this short survey.

In case you have any questions about the project, please do not hesitate contact the project team at ManSciReP@informs.org.

Next

Your full name:

Your email address:

Your affiliation:

Please do not use abbreviations. For multiple affiliations uses a semi-colon (;) to separate the affiliations.

Your current position:

Professor

Associate Professor

Assistant Professor

PostDoc

Other academic with PhD (e.g., lecturer)

Ph.D. Candidate

Professional with Ph.D.

Other:

In what year did you receive your Ph.D.?

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At which departments of Management Science would you typically submit your research paper?

Please **drag&drop** the respective departments to the box on the right, and rank them.

- Departments**
- Accounting
 - Beh. Eco. & Decision Analysis
 - Business Strategy
 - Data Science
 - Entrepr. and Innovation
 - Finance
 - Healthcare Mgmt.
 - Information Systems
 - Marketing
 - Operations Management
 - Optimization
 - Organizations
 - Revenue Mgmt. and Market Analytics
 - Stochastic Models and Simulation

My departments

Which programming language/analysis software/framework do you have access to and are comfortable with?

<input type="checkbox"/> C/C++	<input type="checkbox"/> Jupyter	<input type="checkbox"/> R
<input type="checkbox"/> Fortran	<input type="checkbox"/> Lingo	<input type="checkbox"/> SAS
<input type="checkbox"/> Gams	<input type="checkbox"/> Mathematica	<input type="checkbox"/> SPSS
<input type="checkbox"/> Gauss	<input type="checkbox"/> Matlab	<input type="checkbox"/> SQL
<input type="checkbox"/> Gurobi	<input type="checkbox"/> MS Office	<input type="checkbox"/> Stan
<input type="checkbox"/> Java	<input type="checkbox"/> Python	<input type="checkbox"/> Stata
<input type="checkbox"/> Julia		

Which subscription databases do you have access to?

<input type="checkbox"/> Compustat	<input type="checkbox"/> U.S. Census Bureau
<input type="checkbox"/> CRSP	<input type="checkbox"/> WRDS
<input type="checkbox"/> Factset	

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Management Science Reproducibility Project

Your expectations:

In your estimation, what proportion of Management Science papers **under the current Data & Code disclosure policy** (replication packages required and reviewed for completeness by Code and Data editor) can be **fully reproduced** with the available replication materials?

0 10 20 30 40 50 60 70 80 90 100



In your estimation, what proportion of Management Science papers **under the previous policy** (replication packages expected but not verified or reviewed) can be **fully reproduced** with the available replication materials?

0 10 20 30 40 50 60 70 80 90 100



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Management Science Reproducibility Project

We thank you for registering as a reviewer for the Management Science Reproducibility project.
Your registration has been recorded. We will be in touch in due course.

In case of any questions, please contact the project team at ManSciReP@informs.org.

E.3 Reproducibility report survey

Management Science Reproducibility Project

Welcome to the report survey for the **Management Science Reproducibility Project**.

Here we ask you about your attempt to reproduce the results of your assigned Management Science article.

Before you start completing this report survey, **please familiarize yourself with our [guidelines for reviewers](#)**.

Please enter your email address:

Please enter the DOI of the article (10.1287/mnsc.XXXX.XXXX) that you reviewed:

Please enter the title of the article:

If there was a second person that significantly contributed to this review and should be given credit, please list the name, email address, and affiliation.

What is your overall assessment of the reproducibility of this article's main results (tables, figures, other results in the main manuscript)?

- Fully reproduced.
- Largely reproduced, with minor issues.
- Largely not reproduced, with major issues.
- Not reproduced.
- Not reproduced but consistent with log files.
- Not based on any data analysis, simulation, or code.

Next

Management Science Reproducibility Project

The package includes a README file:

- Yes
- No

Was the README file sufficiently helpful to facilitate the reproduction?

- Yes
- No

Any comment on the README file?

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Management Science Reproducibility Project

Does the replication package already include all the necessary DATA to reproduce the results reported in the main manuscript?

- Yes
- No, the analysis does not need data.
- No, the package includes only partial data.
- No, the package includes only sample or synthetic data.
- No, the package includes no data at all.

The missing data ...

- Can be obtained for free from publicly available sources.
- Can be obtained from a commercial provider against a one-time fee or for a subscription fee.
- Can be obtained in a different way (e.g., upon request to the data owner (not authors!), etc.).
- Cannot be obtained.

Please list the data sources used in the study. (E.g., "lab experiment", "own survey with representative panel", "Comstat, CRSP", ...)

Any other comments on data availability?

Were you able to obtain all data needed to attempt a reproduction of all results?

Yes

No

If applicable, can you please explain any obstacles you had to overcome, or obstacles you could not overcome, in obtaining a complete dataset for review?

Are log files provided from the authors' own running of the code on the original data, such that one can still compare results reported in the paper with the log file in case data cannot be obtained and/or the result cannot be reproduced?

Yes, log files are provided for all results.

Log files are provided for some results, but not for others.

No, log files are not provided within the replication package.

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Management Science Reproducibility Project

Does the replication package include necessary CODE to reproduce the results reported in the main manuscript?

Yes.

No, code is not needed to reproduce results.

No, code is only partially provided.

No, code is not provided.

Which type of code is provided?

C/C++

Lingo

R

Fortran

Maple

SAS

Gams

Mathematica

SPSS

Gauss

Matlab

SQL

Gurobi

MS Office

Stan

Java

Perl

Stata

Julia

Python

Other

Jupyter

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Next

Management Science Reproducibility Project

How many tables does the main manuscript contain overall?

How many figures does the main manuscript contain overall?

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Next

Management Science Reproducibility Project

For each TABLE in the paper, please indicate whether it is a results table (that should be reproducible), whether you were able to reproduce it, and provide any details/comments on obstacles/issues.

	Reproducible?	Can you provide any comments/details?
Table 1	<input type="text"/>	<input type="text"/>
Table 2	<input type="text"/>	<input type="text"/>
Table 3	<input type="text"/>	<input type="text"/>

Any further comments on the reproduction of tables?

Back

Next

Management Science Reproducibility Project

For each FIGURE in the paper, please indicate whether it is a results table (that should be reproducible), whether you were able to reproduce it, and provide any details/comments on obstacles/issues.

	Reproducible?	Can you provide any comments/details?
Figure 1	<input type="text"/>	<input type="text"/>
Figure 2	<input type="text"/>	<input type="text"/>
Figure 3	<input type="text"/>	<input type="text"/>

Any further comments on the reproduction of figures?

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Management Science Reproducibility Project

How many OTHER RESULTS reported in the text of the main manuscript (e.g., p-values from statistical tests not yet reported in the tables / figures) did you identify and attempt to reproduce?

How many of these results were you able to fully reproduce?

Any comments / details on the reproduction of other results reported only in the text?

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Management Science Reproducibility Project

Please upload **one single file** (pdf, zip, etc.) that contains the log files / screenshots / outputs from your analysis that you used to check the tables and figures of the manuscript.

Drop files or click here to upload

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Management Science Reproducibility Project

When attempting reproduction of this paper's results, did you have to change/fix any CODE (other than changing the working directory, etc.)?

Yes

No

Any comments / details on type and extent of code changes?

When attempting reproduction of this paper's results, did you have to change / fix / transform any DATASETS?

Yes

No

Any comments / details on type and extent of dataset changes?

Approximately, how much time (in hours) did you devote to the reproduction of this paper?

On a scale from 0 to 100, how **straightforward/complicated** was it to follow the instructions and reproduce the results?

0 = not straightforward/very complicated 100 = very straightforward/not at all complicated
0 10 20 30 40 50 60 70 80 90 100

On a scale from 0 to 100, how would you rate your **familiarity/expertise in terms of the topic** of the article?

0 = unfamiliar with topic 100 = expert in topic
0 10 20 30 40 50 60 70 80 90 100

On a scale from 0 to 100, how would you rate your **familiarity/expertise in terms of methods and software** used in the article/replication package?

0 = unfamiliar with software 100 = expert in software
0 10 20 30 40 50 60 70 80 90 100

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A full printout of the report survey is included at the end of this document. A personalized link to the survey is provided in your assignment email.

Paper/reviewer details: The first part of the survey just asks to identify yourself and the article/replication package you reviewed.

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