Q Open, 2024, **5**, qoae029
https://doi.org/10.1093/qopen/qoae029
Advance access publication date: 29 October 2024
Article

Open science in agricultural economics

Robert Finger [1,*], Arne Henningsen [2], Julia Höhler [3], Robert Huber [1], Jens Rommel [4] and Carola Grebitus [5]

[1]Agricultural Economics and Policy, ETH Zürich, Switzerland
[2]Department of Food and Resource Economics, University of Copenhagen, Frederiksberg C, Denmark
[3]Business Economics Group, Wageningen University, Wageningen, The Netherlands
[4]Department of Economics, Swedish University of Agricultural Sciences, Uppsala, Sweden
[5]Arizona State University, Morrison School of Agribusiness, Mesa, Arizona, USA

*Corresponding author: Robert Finger, ETH Zürich, Agricultural Economics and Policy. Sonneggstrasse 33, 8092 Zürich, Switzerland. E-mail: rofinger@ethz.ch

Received: August 5, 2024. **Accepted:** October 22, 2024

Abstract

We provide a 'big picture' of what Open Science is and what benefits, limitations, and risks it entails for agricultural economists. We show that Open Science comprises various aspects, such as the accessibility of science, transparency of scientific processes, open and findable, accessible, interoperable, and reusable (FAIR) research data and code, and openness in teaching and education. We identify potential benefits of Open Science for individual researchers and the public, as well as adoption barriers. We highlight that public benefits of a widespread uptake of Open Science practices still remain unexplored. We share best practice examples for key aspects of agricultural economic research, i.e. primary data collection and analysis, optimization and simulation models, use of replication packages, and an Open Science Community. Assessing the author guidelines of twelve agricultural economics journals for their Open Science practices, we find that data citation and transparency are considered important in many journals already, whereas replication, pre-registration, or results-blind reviews are encouraged but rarely enforced. It also becomes evident that the journals differ in terms of how strictly they enforce their open science guidelines. We close by providing recommendations for researchers, journal editors, policymakers, universities, research institutes, and funding agencies to better align public benefits with private incentives.

Keywords: Open science, Meta-science, Replication, Reproducibility, Replicability, Journal ranking, Transparency

JEL code: Q1, A1, C18

1. Introduction

Agricultural economics research provides the basis for advice to farmers, industry, and policymakers (Chavas, Chambers, and Pope 2010; King et al. 2010; Sumner, Alston, and Glauber 2010; Abdulai and Mishra 2020; Dorfman et al. 2024). The accessibility, transparency, and credibility that underpin agricultural economics research are thus essential to produce trustworthy information for academia, policy, and society (Ferraro and Shukla 2023). Open Science practices are key to overcoming the current credibility and reproducibility crisis (Baker 2016; Ferraro and Shukla 2023; Ankel-Peters, Fiala, and Neubauer 2024). Therefore, national and supranational institutions, science funding agencies, and universities worldwide are committed to Open Science (Eisfeld-Reschke, Herb, and

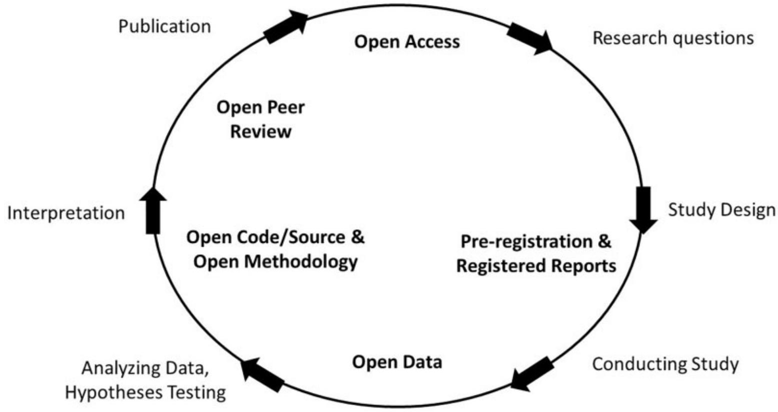

Figure 1. Exemplary 'cycle' of scientific research and possible steps towards Open Science.

Wenzlaff 2014; OECD 2015; European Commission 2016; European Commission 2019, 2021; NSF 2023). In addition, Open Science creates benefits for agricultural policymaking (El Benni, Grovermann, and Finger 2023). To reach the full potential of new methodological approaches, such as machine learning (Storm et al. 2020) or individual participant data meta-analysis (Garcia, McCallum, and Finger 2024), data need to be available and well-structured.

Open Science is not a single aspect or measure but an umbrella term that brings together concepts, such as openness, transparency, rigour, and replicability; it is operationalized through a combination of research practices (Crüwell et al. 2019). Open Science often extends to accessibility and dissemination of science (e.g. open access publications), transparency of scientific processes (e.g. pre-registration, registered reports, and open review), and openness in teaching and education (e.g. open teaching materials). Open Science should not be seen in a vacuum but as embedded in the general discussion of good scientific practices. This includes, for example, careful planning of research and data collection, and critical reflection on the use of methods and approaches. Figure 1 shows an exemplary 'cycle' of scientific research and possible steps to make it more open, i.e. from study design, data collection, and data analysis to the publication of results (Klein et al. 2018). At all stages, efforts towards open research can contribute to improving transparency and reproducibility (Munafò et al. 2017).

To enable a wider adoption of Open Science practices, it shall also become an essential part of teaching and continuing education for researchers, practitioners, and policymakers. Despite the benefits of Open Science, fostering related practices involves costs and risks, especially for individual researchers. Thus, there are significant barriers in terms of knowledge, awareness, and willingness to engage in Open Science practices (Ferraro and Shukla 2023; Heckelei et al. 2023). Currently, benefits of engaging in Open Science for individual researchers often do not outweigh the costs of adhering to such standards. This might explain why, despite potential public benefits, current engagement in Open Science is below the social optimum. Specific Open Science practices have already been introduced by various institutions, universities, and journals, but agricultural economics as a whole is not yet operating at the frontier (Finger, Grebitus, and Henningsen 2023; Ferraro and Shukla 2023; Heckelei et al. 2023; see also Section 4).

This article discusses avenues to promote Open Science in agricultural economics, thereby contributing to the growing literature on improving credibility, replication, reproducibility, and openness (Abdulai and Mishra 2020; Lybbert and Buccola 2021; Finger, Grebitus, and Henningsen 2023; Ferraro and Shukla 2023; Heckelei et al. 2023; Arpinon and Lefebvre 2024; Dreber and Johannesson 2024). To this end, we provide an overview of Open Science in agricultural economics, investigate practices of agricultural economics journals, identify examples of best practices, and outline pathways for future developments, including implications for research and policy. We offer insights for researchers, students, journal editors, policymakers, and science management at universities, research institutes, and funding agencies.

We proceed as follows: Section 2 presents a definition of Open Science and elaborates what it entails. Section 3 identifies why and how Open Science can benefit the discipline of agricultural economics and which barriers to adopting Open Science practices exist. Section 4 reviews the current state of Open Science practices in agricultural economics journals, and Section 5 provides best practice examples for Open Science in agricultural economics. Finally, Section 6 presents a way forward, including implications for policy and research.

2. What is Open Science?

Two definitions of Open Science are essential in the context of this article. First,

> Open Science refers to the process of making the content and process of producing evidence and claims transparent and accessible to others (Munafò et al. 2017: 5)

And, second,

> Open Science is a system change allowing for better science through open and collaborative ways of producing and sharing knowledge and data, as early as possible in the research process, and for communicating and sharing results (European Commission 2019: 1)

This implies that Open Science is a broad concept that encompasses several practices, including open access, open data, open code and software, open methodology, open peer review, open educational resources, and the teaching of open science (Table 1). Adopting Open Science often involves a combination of different practices and a gradient of their implementation.[1] Therefore, a fundamental dichotomy between adoption and non-adoption may not be useful. Furthermore, what is and what is not included in the continuum of Open Science practices is context-specific. Table 1 offers brief explanations of key Open Science practices.

In the following, we provide context for the above-listed Open Science practices in agricultural economics.

Open access for journal publications can be provided through different pathways. *Green open access* offers self-archiving of pre-prints and (often after an embargo period) post-prints of accepted versions after peer review but before editing by the publisher of restricted access publications, e.g. on the websites of the authors or their institutions. *Gold open access* means that authors pay for open access of their papers, and *diamond/platinum open access* means that neither authors nor readers pay. All agricultural economics journals offer some open access publishing options, usually both green and gold open access are options. Examples for diamond/platinum open access journals are *Bio-based and Applied Economics* and the *German Journal of Agricultural Economics*.

While *open methodology* requires scientific publications to be fully transparent about the methodology, this is often not the case. To foster open methodology, several journals incentivize pre-registration including a pre-analysis plan that details the methods. Depending on the pre-analysis plan, this provides in-depth information on data collection and analysis. For example, the *Spanish Journal of Agricultural Research* requires a primary data analysis that is not pre-registered to be clearly labelled as exploratory research (Barreiro-Hurlé 2021). *Q Open* explicitly welcomes registered reports, which are documents that describe research strategies for data collection and analysis before the data has been

Table 1. Exemplary elements of Open Science practices.

Open Science Practice	Explanation
Open access	Providing unrestricted availability of research products for the entire public by removing barriers (e.g. financial and legal) to access. Open access is linked to the use of open licences, e.g. the Creative Common Attribution Licence.
Open methodology	Describing data collection protocols in detail to allow replication, and describing the analysis (from raw data to figures and tables in the published work) in a transparent and reproducible way, so that others can easily understand and reproduce the analysis, and can easily use the methodology for their own analyses. This should be done as early as possible and preferably already before the researcher has access to the data.
Open code	Making computer code used in an analysis publicly available. Codes for a particular analysis can be used for replication purposes or as a starting point for performing similar analyses. Releasing code in the form of an easy-to-use and well-documented way, for example, a software package that implements a newly developed and widely applicable method.
Open research data	Making data that underpins scientific research results publicly available without restriction in terms of access.
Open peer review	Openly identifying authors and reviewers; publishing review reports along with an article; open participation of the wider community in the review process.
Open educational resources	Making educational resources, such as textbooks, lecture notes, slides, and other material openly available.
Teaching open science	Preparing upcoming generations of students and researchers for the requirements of Open Science by including related courses in the curriculum.

Sources: Crüwell et al. (2019), Tennant et al. (2016), Protzko et al. (2023), and NSF (2023).

collected. It is important to note that full compliance with open methodology requires that all details of the analysis are clearly described in pre-analysis plans and registered reports as well as in scientific articles so that others can fully understand and replicate the analysis.

Open code refers to the publication of the computer code used to conduct the analysis. Technically, it is possible for field experts to translate a well-written description of an analysis (open methodology) to code. Despite the close link between open methodology and open code, it is important to strive for both because one cannot expect readers to refer to the code for understanding the methodology and it is inefficient to rewrite code for replications or for similar studies. An increasing share of publications in agricultural economics has corresponding replication packages that include code and related data to enable readers to replicate the published analyses. While only a few agricultural economists create and publish open-source software packages based on their research, e.g. for Stata or R, many agricultural economists use open-source software packages that were created and published by others (often non-agricultural economists). Examples for R packages with contributions from agricultural economists are ‘sampleSelection’ (Toomet and Henningsen 2008), ‘frontier’ (Coelli and Henningsen 2020), and ‘sfaR’ (Dakpo et al. 2023).[2]

While *open research data* imply that the data used in a scientific analysis are accessible by the public,[3] datasets are often owned by a private company (e.g. GfK consumer panel data and scanner data from retailers) or are confidential and can only be accessed through a public authority, e.g. Farm Accountancy Data Network (FADN) data. Nevertheless, a publication should describe how others can access the data, e.g., by requesting an identical version of a dataset. If a dataset is owned by the researcher but cannot be made publicly available, e.g. due to the European Union's General Data Protection Regulation or approvals by institutional review boards, this should be clearly explained. If data cannot be anonymized because variables that are essential for the analysis allow individual survey participants to be identified, data processing agreements with other researchers who want to access the data can be a solution to ensure confidentiality of the dataset.

So far, there are no examples for *open peer review* from agricultural economics journals but only from related fields (*Economics—The Open-Access, Open-Assessment Journal*—https://www.degruyter.com/journal/key/econ/htm, *Biogeosciences*—https://www.biogeosciences.net/). In this regard, Peer Community In (PCI, https://peercommunityin.org/) is worth mentioning. A critical mass of researchers in a field is needed to start what is called a *community*. This community reviews and recommends preprints. Recommended preprints can be transferred to the community's peer community journal or can be submitted to other journals. Some journals are PCI-friendly; i.e. recommended preprints are reviewed faster or will be accepted without review. There is no peer community for agricultural economics, yet, and no journals in agricultural economics have indicated that they are PCI-friendly.

With regards to *open educational resources*,[4] there are many different ways of making educational resources freely available, e.g. through personal websites, online learning platforms such as Coursera, and general content-sharing platforms such as youtube.com. The diverse, decentralized, and currently limited publication of educational resources in agricultural economics makes it difficult to find relevant educational resources. The challenge of identifying suitable educational resources is further aggravated by a general intransparency, particularly regarding the quality. Some centralized registers or platforms, perhaps with some elements of quality control or quality rating, could make it easier to find suitable open educational resources. When educational resources include parts from other resources, licence issues may prohibit making the resources openly available (e.g. Hüttel and Hess 2024).

Finally, while we are not aware of concerted efforts towards *teaching open science* in agricultural economics, several colleagues are already covering topics, such as ethics, pre-analysis plans, and GitHub, for instance in classes for bachelor, master, or doctoral students, or by offering pre-/post-conference workshops and the like.

Findable, accessible, interoperable, and reusable principles

The examples of Open Science showcase different ways to make research more accessible, but demanding Open Science alone is ineffective if the openly available material cannot be found or is unusable. Hence, institutions, such as the European Commission, advocate strongly for findable, accessible, interoperable, and reusable (FAIR) principles (Council of the European Union 2016). Key aspects to ensure FAIR features include the use of persistent digital identifiers and metadata (Schwardmann 2020)[5]. There may also be situations where science is open but does not fulfil the FAIR principles. For example, data may be openly available but not interoperable because they are available only as scanned documents or stored in a file format that is inaccessible to most researchers, or the data cannot be found because no metadata was used when it was made available. In these cases, the open data are largely useless. Along these lines, code being open may not be useful per se, in most cases important information around it is needed (along the lines of open methodology)[6]. The optimum, of course, is a situation where data, scientific software, and code are both open and FAIR (Fig. 2).

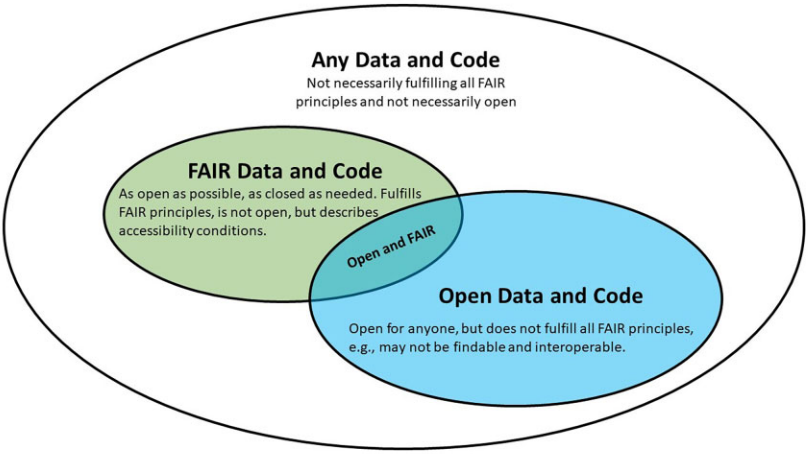

Figure 2. Exemplary illustration of open and FAIR data and code.

3. Benefits and adoption barriers of Open Science

Open Science offers benefits to individual researchers, but there are also large positive externalities (benefits for science, society, and policymaking) that are not internalized by the individual researchers. Whether or not to engage in Open Science is to a large extent an individual decision. In many settings, the public benefits of Open Science outweigh the costs for individual researchers, but the benefits for individual researchers of engaging in Open Science are often small. In other words, the optimal decisions by individual researchers regarding Open Science practices may result in smaller Open Science engagement than in the social optimum (Fig. 3). Therefore, we ought to increase our efforts to better align individual incentives with public benefits.

3.1 Public benefits of Open Science

Open Science is ushering in a new era of scientific endeavours that promises a wealth of public benefits (OECD 2015; NSF 2023). It accelerates the pace of discovery and

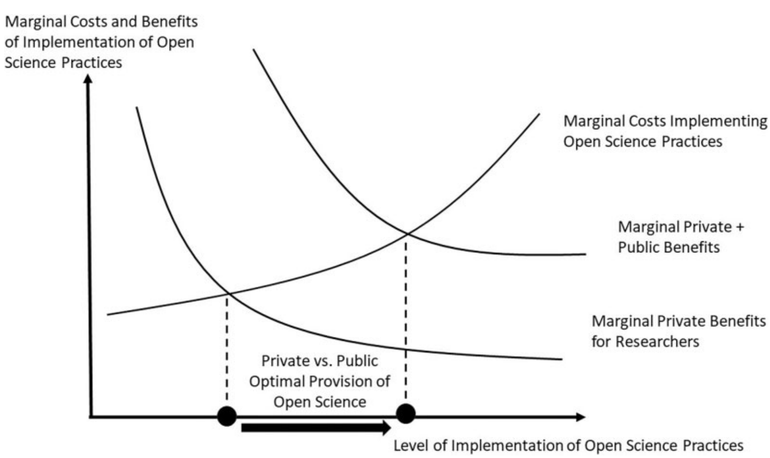

Figure 3. Marginal costs and benefits of implementation of Open Science practices and private and social optima.

promotes efficiency by eliminating redundant data collection, allowing for a deeper understanding of research, and encouraging more research using existing data and software resources (OECD 2015; Miguel 2021). It also opens avenues for valuable comparative perspectives, such as in the Agricultural Model Intercomparison and Improvement Project (AgMIP, https://agmip.org/) that has established research standards that allow different research groups to use the same assumptions across regions and models, but to also continuously improve individual models (Rosenzweig et al. 2013). Another well-known example is the Global Trade Analysis Project (GTAP, https://www.gtap.agecon.purdue.edu/), in which researchers have established a standard modelling approach that has improved data availability and research results in the context of trade, development, and global environmental challenges (Aguiar et al. 2022). Open Science also enhances quality and integrity within the scientific community. By subjecting research to wider evaluation and scrutiny, it reinforces the self-correcting principle inherent in science, thereby increasing its verifiability and credibility (Miguel 2021; Peterson and Panofsky 2021). The adoption of open and FAIR science practices forces researchers to invest more effort before publication, thereby reducing errors and increasing the overall robustness of results (Munafò et al. 2017).

The impact of Open Science extends far beyond the scientific community (OECD 2015). For instance, increased reliability and reusability of scientific work can improve agricultural policy decisions (Finger, Grebitus, and Henningsen 2024). By providing reliable, open, and accessible decision-making tools for industry, society, and policymakers, Open Science also enables stakeholders to address complex challenges more effectively (OECD 2015). Transparency is at the heart of Open Science, fostering public disclosure and engagement, which ultimately increases confidence (Munafò et al. 2017). In addition, open and FAIR science acts as a catalyst for new research methodologies, enabling the use of cutting-edge technologies, e.g. by providing large amounts of well-structured data that can be used in machine learning approaches for automated text search and data mining, as well as the use of new approaches to meta-analysis (e.g. on individual participant data) (Storm, Baylis, and Heckelei 2020; Garcia, McCallum, and Finger 2024). Therewith, Open Science can foster new meta-research in agricultural economics, leading to new and more reliable insights and discoveries. Crucially, Open Science transcends geographical and socio-economic barriers to deliver inclusive benefits globally (OECD 2015). For example, students and researchers with limited resources could greatly benefit from having access to open educational resources, open access publications, and well-documented open code that they can learn from and build upon.

3.2 Benefits of Open Science for individual researchers

In addition to public benefits, there are several benefits for the individual researcher (Allen and Mehler 2019; Miguel 2021). For instance, following Open Science principles usually leads to a better organization of data and code files and, thus, can make it easier for researchers to revise their analyses (e.g. based on comments from reviewers) or to re-use their own data and code for other papers (Miguel 2021). Adhering to Open Science guidelines can also ease compliance with requirements by entities, such as funding agencies and universities (Eisfeld-Reschke, Herb, and Wenzlaff 2014; European Commission 2016, 2019, 2021; NSF 2023). Those who adhere to Open Science practices could be more successful in the publishing process if it results in manuscripts that are more detailed and precise in describing data, methods, and analyses. This also comprises signalling of high scientific standards to editors and reviewers. Furthermore, several top-tier journals, e.g. in general economics, request adherence to certain Open Science practices (Vilhuber 2021, 2023).

Another benefit of following Open Science principles might be more frequent citations. While some studies find that open access publications are more frequently cited than closed access publications (e.g. Tennant et al. 2016), other studies do not find a difference, particularly when accounting for selection bias regarding the choice of open and closed access publications (Gaulé and Maystre 2011; for a review see Langham-Putrow, Bakker, and Riegelman 2021). However, there is some evidence that open access publications are cited by more diverse sources than closed access publications, indicating a wider use of published results (Huang et al. 2024). While there is already evidence that studies that follow open data principles get more frequently cited (Piwowar, Day, and Fridsma 2007; Zhang and Ma 2013; Christensen et al. 2019; Colavizza et al. 2020; Zhang and Ma 2021), we are not aware of empirical studies that investigate the effect of open code or open methodology on citations. While Park and Wolfram (2019) find that research software is rarely cited, articles that accompany scientific software are often frequently cited (as can be seen, e.g. by high-impact factors of journals that publish this type of papers, such as the *Journal of Statistical Software*)[7].

When following Open Science practices, some journals award badges (Munafò et al. 2017) to highlight open data, open materials, and pre-registrations. Collaborative research often entails sharing materials, code, and data. Hence, researchers who practise Open Science might become more sought-after as collaborators (OECD 2015).

3.3 Barriers to adopt Open Science practices

The adoption of Open Science practices can be hindered by several barriers (Allen and Mehler 2019; Anzt et al. 2020). For instance, the individual researcher might simply lack resources. Open Science can be time-intensive and can imply additional costs, e.g. to upload and store data for public access or article processing charges for gold open access publications (Allen and Mehler 2019). Furthermore, navigating Open Science guidelines can be difficult (Klein et al. 2018). Lack of recognition for the adherence to Open Science practices, for example, in hiring and promotion decisions, can also deter researchers from doing so (Allen and Mehler 2019).

It is important to keep in mind that researchers who are more open than others about their workflow, e.g. by sharing all materials used to collect data, the data itself and code used for analysis, are making themselves more vulnerable (Gewin 2016). While the detection of errors and weaknesses is beneficial for the scientific community and society as a whole, this can be detrimental for individual researchers, for example, when a paper is rejected during the review process or retracted after publication. As long as there are no requirements for all to adhere to the same standards, this is a key challenge.

Furthermore, having to share data that researchers spent considerable time on to collect means that these researchers lose their advantage of publishing studies based on the same dataset before others can do this. This can have serious consequences, not only for individual researchers but also for society as this might reduce incentives to collect important data (Christensen et al. 2019). Hence, it is important to protect authors who collect their own data. For example, this could be ensured by releasing the dataset under a copyright that restricts the use of the dataset throughout a reasonable embargo period during which the author keeps the sole right to use the dataset for publishing new research (Miguel 2021). An example of how this is done in other fields can be found here for *Marketing Science* (https://services.informs.org/dataset/mksc/download.php?doi=mksc.2023.0045).

Finally, an attitude–behaviour gap has been observed (Brinkman et al., 2021; Heckelei et al. 2023). While many researchers would value highly open and FAIR science practices, this does not imply that these practices are well-known or widely applied.

4. Open Science in agricultural economics journals

The policies and guidelines of scientific journals, e.g. regarding Open Science, can largely affect the practices and norms in the scientific community (Miguel 2021). For instance, Ankel-Peters, Fiala, and Neubauer (2023) discuss how much economists replicate and what incentives economics journals provide for different types of replication. They scan forty-two leading economics journals for the number of ‘policing replications’, i.e. replications that directly question the result of an earlier article. Only 0.9 per cent of the scanned articles are policing replications, and replication is currently rarely mentioned in journal policies, although a majority of journals is generally open to publish replications and comments challenging earlier articles. Ankel-Peters, Fiala, and Neubauer (2023) conclude that economics lacks incentives to encourage a sufficiently high number of policing replications. Similarly, there is a lack of replication in political science (Brodeur et al. 2024).

To evaluate the status quo of Open Science implementation in agricultural economics, we assess the policies and guidelines of twelve agricultural economics journals, therewith also complementing the assessment of Arpinon and Lefebvre (2024), who focus on pre-registration and registered reports covering a wider range of journals, the theoretical assessment of Hüttel and Hess (2024) focusing on artificial intelligence-related challenges in scientific publishing, and the assessments of Brodeur et al. (2024) for political science and Ankel-Peters, Fiala, and Neubauer (2023) for economics in general. To create a list of agricultural economics journals, we follow Finger et al. (2022), who suggest ten leading agricultural economics journals,[8] and add the recently launched open access journals by the European Association of Agricultural Economists (*Q Open*) and the Agricultural and Applied Economics Association (*Journal of the Agricultural and Applied Economics Association* [*JAAEA*]). To evaluate the status quo of Open Science implementation in these journals, we apply the Transparency and Openness Promotion (TOP) guidelines and factors. The TOP factors build on the eight TOP guidelines criteria described in Nosek et al. (2015), and are a set of metrics to assess open science practices. The TOP factor rubric for evaluating the author guidelines lists ten categories of practices[9] and uses scores for the level of implementation (Mellor et al. 2024). A value of 0 applies if a practice is solely encouraged or not mentioned, a value of 3 describes that a practice is enforced by the journal. Values of 1 and 2 describe intermediate steps that differ in their level of implementation. A detailed description of each value per category can be found in Appendix 1.

Three co-authors of this article independently assessed the journals’ online guidelines for authors based on the ten TOP factor categories. Following their independent coding in the beginning of May 2024, these co-authors discussed all cases where their coding did not match to achieve consensus. Next, the results of the evaluation were sent to editors-in-chief of the assessed journals for feedback and potential correction. Initially, seven replied. After a reminder in June, four more replied. Thus, all but one journal reacted to the correspondence. Editors were made aware of the scores using the TOP criteria, and were offered the opportunity for feedback. Those who replied informed us about their opinion on the rating. Two editors proposed a total of five changes of which three were accepted after review from the co-authors. Table 1 provides an overview of compliance with the ten TOP criteria of the twelve journals. Note that in response to our exchange with editors on the topic, some journals may already have adjusted their guidelines by the time this article is published.

Based on the assessment, we find varying degrees of prevalence of the evaluated practices. A few journals are forerunners implementing almost all practices. The *JAAEA* (1.4) and the *American Journal of Agricultural Economics* (*AJAE*) (1.2) have the highest average scores, while *Agricultural Economics* (0.2) and *Food Policy* (0.2) have the lowest average scores. Almost all journals encourage data citation and data transparency, but the submission of code (analytical code transparency) and material transparency are required less often. Only one journal (*AJAE*) provides information on reporting guidelines, such as PRISMA (for systematic literature reviews) or CONSORT (for randomized trials).[10] Pre-registration, replication studies, and measures to mitigate publication biases, such as registered reports, are mentioned in a few author guidelines (explicitly and affirmatively for instance in *Q Open*; the *Journal of Agricultural Economics* mentions ‘clinical trial registration’). In general, the many zeros and few Level 3 categorizations show that there is still room for improving on several Open Science practices. Feedback from editors indicated an awareness of the challenges and potential solutions.

Overall, the discussion of differing assessments revealed that it can be challenging for authors to interpret the guidelines provided on a journal's website. For example, does 'expected' mean the same level of implementation as 'required'? And how strictly are these policies enforced? This also affected the evaluation based on the TOP factors, which offer room for interpretation and overlap in some instances. A standardized terminology or reference to the TOP rubric levels, as well as a revised rubric, could help to better assess journals in the future.

To improve author guidelines, a concerted effort across all journals in the field may be needed. Guidelines ought to be written in a manner that they are easily understandable and accessible for authors, e.g. with respect to phrases such as 'authors are expected to …' where there may be different interpretations as to how strict the enforcement would actually be. Along these lines, specifying consequences for non-compliance, such as not accepting a manuscript for publication, could be spelled out more explicitly.

We also observe differences between publishers. Large publishers, such as Wiley, have developed a number of general guidelines on Open Science. The author guidelines of agricultural economics journals often refer to these general publisher guidelines, but sometimes it remains unclear to what extent they apply to a specific Wiley journal. For instance, guidelines may contain detailed instructions on how to deal with animal testing ethics or human clinical drug trials, which may not always be relevant for social scientists. Providing guidelines that are adapted to disciplinary norms and terminology therefore remains an important task. Again, concerted efforts across journals in the field of agricultural economics would be beneficial.

5. Four best practice examples in agricultural economics

In this section, we present insights from four best practice examples highly relevant for the field of agricultural economics, ranging from best practices when (1) collecting and analysing primary data, (2) using agent-based models, (3) creating replication packages, and (4) creating a local Open Science Community. While the collection of these practices is based on the reviewed literature and our own experience—hence it is to some extent subjective and incomplete—its purpose is to encourage a debate on Open Science practices in agricultural economics and to showcase where improvements are possible.

5.1 Best practices when collecting primary data

Many agricultural economists collect primary data from farmers or consumers to answer research questions. This section describes an Open Science workflow and highlights good practices for research designs that involve surveys or experiments, deductively testing clearly specified hypotheses. We also discuss extensions to cases, where secondary micro-level data (such as FADN), macro data, or even qualitative data are used.

Open Science workflows and practices start in the design phase of research. After defining the research questions, the main outcomes (typically serving as dependent variables in causal analyses) should be defined. Examples are contributions to a public good in an experiment, options in a discrete choice experiment, or the adoption of a management practice in a survey. Furthermore, a theoretical or conceptual model—sometimes also called the scientific model in contrast to a statistical model (cf. McElreath 2018)—should be developed because it can be used to specify key explanatory variables (typically understood as treatments in causal inference) and other covariates (it is good practice to think about good and bad controls, cf. Cinelli et al. 2024). In an experiment, this can be as simple as the impact of a treatment on the outcome. Specifying such models for instance in directed acyclic graphs

Table 2. TOP factor evaluation of leading journals in agricultural economics.

Journal name criterion	*AGB*	*AE*	*AJAE*	*AEPP*	*AJARE*	*CJAE*	*ERAE*	*FP*	*JARE*	*JAE*	*JAAEA*	*Q Open*	Average
Data citation	2	0	2	2	2	2	0	1	1	2	2	2	1.5
Data transparency	2	2	2	1	2	2	2	0	2	2	2	1	1.7
Analytical code transparency	0	0	2	1	0	0	2	0	2	2	2	0	0.9
Materials transparency	0	0	2	0	0	0	2	0	0	2	0	0	0.5
Reporting guidelines/design and analysis transparency	0	0	1	0	0	0	0	0	0	0	0	0	0.1
Study pre-registration	0	0	1	0	0	0	0	0	0	1	0	0	0.2
Analysis plan pre-registration	0	0	1	0	0	0	0	0	0	1	0	0	0.2
Replication studies	0	0	1	0	0	0	0	0	0	0	3	3	0.6
Publication bias	0	0	0	0	0	0	0	1	0	0	3	3	0.6
Open science badges	0	0	0	0	0	0	0	0	0	0	2	0	0.2
Average	0.4	0.2	1.2	0.4	0.4	0.4	0.6	0.2	0.5	1.0	1.4	0.9	0.6
Total	4	2	12	4	4	4	6	2	5	10	14	9	

Note: *AGB* = *Agribusiness*; *AE* = *Agricultural Economics*; *AJAE* = *American Journal of Agricultural Economics*; *AEPP* = *Applied Economic Perspectives and Policy*; *AJARE* = *Australian Journal of Agricultural and Resource Economics*; *CJAE* = *Canadian Journal of Agricultural Economics*; *ERAE* = *European Review of Agricultural Economics*; *FP* = *Food Policy*; *JARE* = *Journal of Agricultural and Resource Economics*; *JAE* = *Journal of Agricultural Economics*; and *JAAEA* = *Journal of the Agricultural and Applied Economics Association*. The assessments are based on the authors' evaluations and are not necessarily agreed upon by the editors.

(e.g. Pearl 1995) can help to make assumptions on causal pathways and the identification strategy explicit. It also facilitates the integration of scientific and statistical/econometric models (see McElreath 2018; Huntington-Klein 2021 for practical guidance). Specified materials and theories can be shared for early replication and collaboration.

After specifying a statistical or econometric model, the next step is typically to design the survey instrument or to program an experiment. This will involve trade-offs between being brief and gathering additional useful information. Many analytical choices have to be made, questions have to be worded, and it is good practice to document decisions and trade-offs. Researchers should think about and discuss the statistical power (the probability of finding an effect if it is there) of the research design. This can range from a calculation under strongly simplified assumptions to more advanced research designs (Faul et al. 2007) or simulations. Synthetic data generation and writing analysis code before data collection can be useful to spot mistakes in the design and to ensure a good workflow integration with pre-analysis plans, pre-registration or registered reports. These practices ensure Open Science workflows and allow for sharing research designs with peers early in the process.

A pre-analysis plan should be written before data collection commences. This plan specifies the main models to be estimated or tests to be applied. A pre-registration, often following pilot testing and making adjustments to the original plan, can then be used to publicly document the analysis before the data are being collected. Overall, a pre-registration can range from a very basic description of key hypotheses (e.g. https://aspredicted.org) to more advanced plans (e.g. Open Science Framework [OSF: https://osf.io/] or American Economic Association's [AEA] registry for randomized controlled trials [RCT registry]). Plans should be as explicit as possible about outcomes and their hierarchy, planned analyses, correction for multiple testing, sample size determination, and treatment of outliers. An excellent early discussion of pre-analysis plans in economics can be found in Olken (2015). A recent review of the practices is given by Ofosu and Posner (2023).

After data collection, the analysis is ideally conducted with pre-programmed code and results are reported. Hence, in many cases engaging with pre-analysis plans does not imply more work; instead the workload is frontloaded. This shift from engaging with the analysis part more extensively before data collection can help identify errors and facilitates peer feedback when it is most useful (e.g. through registered reports, cf. Arpinon and Espinosa 2023; Arpinon and Lefebvre 2024). Note that pre-registration shall not be understood as limiting analytical freedom. Additional analysis, robustness checks, and the like are all still possible and encouraged; the main advantage is simply that deductive pre-specified analyses can be clearly distinguished from explorative additional analyses. When publishing a paper, ideally all data, instruments, and analyses are shared with peers and readers. Again, there is a range of possible practices from making a zip file available at the journal's website or at an intuitive repository, such as researchbox.org to more advanced platforms with a wide range of sharing opportunities, such as the OSF. In any case, it is best practice to document data and code carefully and extensively (see Section 5.3 for further details).

The described practices are mainly applicable to quantitative primary data collection efforts. However, even for qualitative research, it is possible to pre-specify key analytical steps (Jacobs 2020). In addition, for secondary data, such as the data from the FADN (which the researcher typically has to apply for), many of the practices can be followed as well before the data are analysed or even obtained. Similarly, pre-registration of analyses of future data can enhance the credibility of research designs. Think for instance of a specific reform step of the common agricultural policy. Before new evaluation data become available, researchers could pre-specify how they want to evaluate policy reforms (by pre-registering analysis plans), shielding them both from their own subconscious biases and accusations of selective reporting of results.

5.2 Best practices when using agent-based models

Computer simulation models are an interesting case because they showcase the combination of open methodology and open code. Models, such as farm-level or partial equilibrium models, are a relevant and widely applied methodological tool for ex-ante assessments in agricultural economics (El Benni, Grovermann, and Finger 2023), and agricultural economists are also using agent-based models to simulate farmers' behaviour in response to evolving environmental, economic, and institutional conditions and policies (Huber et al. 2018). Agent-based models are characterized by combining individual behaviors, typically of farmers, with interactions between agents, leading to emergent phenomena that cannot be explained by a single decision-making concept. These 'bottom-up' approaches involve high modelling complexity, making it challenging to adhere to the FAIR principles, particularly regarding accessible, interoperable, and reusable code.

To facilitate transparency in the model and underlying code, the agent-based modelling community employs the Overview, Design concepts, Details (ODD) protocol for documentation (Grimm et al. 2006). An extended version, ODD+D, which includes standardized descriptions of human decisions (Müller et al. 2013), is now the standard for presenting models with an agricultural economics foundation, such as MP-MAS, AgriPoliS, or FARMIND[11]. The ODD protocol is designed to simplify the writing and reading of agent-based model descriptions, facilitating model replication without being overly technical. They are independent of the hardware and software used to implement the model (Grimm et al. 2020). Agent-based modellers also use platforms like the Network for Computational Modeling in the Social and Ecological Sciences (CoMSES Net) to share their source code and replication packages. This open code practice enables other scientists to validate and build upon existing models, fostering collaboration and transparency. Over 100 models related to agricultural economics are available on the CoMSES Network.

Additionally, the agent-based modelling community commonly uses NetLogo, a popular modelling language known for its user-friendly interface and extensive community support. NetLogo promotes consistency across studies and facilitates collaboration. However, most of the agent-based models published in agricultural economics journals are based on long-term developments of a core model within a research group. For example, the agent-based model MP-MAS has been utilized in nearly fifty studies by the same research group (e.g. Schreinemachers and Berger 2011; Troost and Berger 2015). AgriPoliS has been adopted by two research groups, though its primary development remains within a relatively closed community of modellers (e.g. Hristov et al. 2020; Appel and Balmann 2023). Notably, AgriPoliS also has a well-documented research data management system making scripts, datasets, and other components directly accessible. While these models are available in repositories, their reuse is challenging due to their complexity, stemming from extensive, long-term development. A community-wide sharing of concepts, methods, and software has not yet been fully established, despite more than 20 years of agent-based models in agricultural economics.

Recent developments in the agent-based modelling community focus on improving documentation of the entire modelling process (Grimm et al. 2014). This includes, for example, keeping modelling notebooks (Ayllón et al. 2021) or protocols for ensuring simulation validity (Troost et al. 2023). In addition, the concept of reusable building blocks has been suggested (Berger et al. 2024). These building blocks are components of an agent-based model that represent specific mechanisms or processes relevant across different modelling contexts. By focusing on single mechanisms or processes, these blocks offer better reusability compared to larger modules or subsystems that encompass multiple mechanisms and processes. However, developing reusable building blocks necessitates effective knowledge sharing and active community involvement to address and overcome the adoption barriers mentioned earlier; a challenge recently also addressed by the Open Modeling Foundation,[12] which seeks to develop standards and best practices among diverse communities of modelling scientists.

5.3 Best practices for replication packages

A replication package consists of a set of files that can be used to replicate a published study. In case of an empirical analysis, a replication package typically consists of one or more data files, one or more code files (e.g. R and Python scripts), and one or more documentation files that describe the before-mentioned files (e.g. the variables in the data files) and give instructions for using these files to obtain the results that are presented in the corresponding study. Hence, replication packages implement open data and open code[13] principles. They can be published as supplementary material along with the published study (e.g. on the publisher's website) or they can be published elsewhere (e.g. on GitHub, Harvard Dataverse, ICPSR [Inter-university Consortium for Political and Social Research], and Zenodo) with the published study referring to the replication package.

The contents of a replication package should replicate all steps of the respective analyses, i.e. the path from 'raw' data to tables, figures, and other results in the respective publication. The special issue 'Replications in Agricultural Economics' has shown that the largest obstacles to replicability occurred in the preparation of the data, i.e. when creating a dataset used for analysis based on raw data (Finger, Grebitus, and Henningsen 2023). While the AEA has detailed instructions for preparing replication packages and conducts pre-publication reproducibility checks for all of its regular journals (Vilhuber 2021, 2023), Table 2 of this article indicates that none of the top agricultural economics journals enforces replication packages (see rows 'data transparency' and 'analytical code transparency'). Hence, only a small proportion of publications in agricultural economics journals is accompanied by a replication package fulfilling open data and open code principles. However, an increasing number of agricultural economists create and publish replication packages along with their articles.

If an empirical analysis is rather 'linear', does not have too many (hundreds) lines of code, and is not too computationally demanding, an easily accessible replication document that includes code, results, and explanations can be created with tools for reproducible research, e.g. Sweave (Leisch 2002), knitr (Xie 2014, 2015, 2024), R Markdown (Xie, Allaire, and Horner 2023), Jupyter Notebook (Kluyver et al. 2016), or Quarto (Allaire et al. 2024). These tools have the advantage that the resulting replication document follows open code principles and makes the empirical analysis and the results transparent even to readers without access to data or software. A publication of the (raw) data along with the replication document is advisable because it enables re-analyses with different methods, individual participant data meta-analyses, and other ways of reusing the data and, thus, follows open data principles.[14] An excellent example for this kind of replication document with an accompanying GitHub repository[15] with data, source code, and further explanations is the supplementary material in Kliem and Sagebiel (2023). If an empirical analysis consists of many steps combined in a 'non-linear' way, consists of hundreds or thousands lines of code, or the execution time of the analysis is long, splitting up the code into separate files could be a more appropriate way of conducting and sharing the analysis than to generate a single file in PDF or HTML format. If many files are provided, a flowchart can be helpful to illustrate how the files are connected to each other. An example for this is the replication package for Gisbert-Queral et al. (2021a), available at Zenodo (Gisbert-Queral et al. 2021b).

5.4 Creating an Open Science Community at Wageningen University

Open Science Communities are local bottom-up groups of researchers, which focus on introducing, disseminating, and promoting Open Science practices (Armeni et al. 2021; International Network of Open Science & Scholarship Communities 2024). Open Science

Communities complement the top-down approach of funders and universities, in that the initiative originates from the researchers themselves. To make Open Science practices visible and to lower the entry barriers for a critical mass of researchers to acquire new Open Science workflows, Open Science Communities rely on a range of activities, such as seminars, workshops, or local journal clubs. As the often voluntary coordination of an Open Science Community requires time, a sustained and efficient community depends on funding core activities and institutional support (Armeni et al. 2021).

The International Network of Open Science & Scholarship Initiative (2024) currently counts thirty-six communities in eighteen countries. One example of Open Science Communities, in which agricultural economists are also involved, is the Open Science Community Wageningen (2024). Founded in 2021, the Open Science Community Wageningen currently consists of ten core members. The Open Science Community starter kit, which is available free of charge at www.startyourosc.com, was used to set up the community. A newsletter regularly informs subscribers about events, funding opportunities, and relevant research results. In addition to lunch seminars and presentations by Peer Community In, for example, a Lighthouse award was presented in 2022. However, full schedules, lack of recognition for practising Open Science, and academic employment cycles make it challenging to obtain the necessary commitment, time, and financial resources. Two initiatives will respond to these key challenges: (1) Start-up funding from the Dutch Research Council (NWO) will allow the Open Science Community Wageningen to consolidate and professionalize the organization. (2) The university's new academic career framework is set out to reward all academic activities and practices, including Open Science (Jetten and Spruit 2023).

6. Conclusion and pathways to Open Science

We propose that Open Science shall become a cornerstone of agricultural economics research and teaching. Open Science combines openness, transparency, rigour, and replicability, and comprises several layers, such as the accessibility of science, the transparency of scientific processes, open and FAIR research data and code, and the openness in teaching and education. However, researchers face costs and barriers when engaging in Open Science. As a result, large potential public benefits of widespread uptake of Open Science practices remain untapped. We demonstrate that the current state of implementing Open Science practices in agricultural economics journals is heterogeneous. While a few journals are at the forefront of encouraging or even mandating the use of Open Science practices, most journals could strengthen this part further. Moreover, we see large heterogeneity across Open Science practices that are encouraged or mandated by journals. For example, while data transparency and data citation are well developed across all journals, the use of pre-analysis plans and pre-registration is fostered by only a few. We share insights into best practice examples in various fields of agricultural economics, ranging from data collection and analysis, optimization and simulation models, the creation of replication packages to the relevance of local Open Science communities.

Our analysis has implications for the agricultural economics discipline. The increasing (and needed) trend to Open Science will imply massive changes in how research is conducted, documented, and communicated. To facilitate this development, researchers shall be provided with tools and advice that make Open Science easy to implement, for example, by providing steps to Open Science tailored to agricultural economics research (Crüwell et al. 2019), and by pushing the use of tools such as aspredicted.org and researchbox.org that aim to make pre-registration and data sharing easy, creating intuitive interfaces and easy access. These steps also shall involve improved training, showcasing and creating hands-on experiences. This certainly involves universities to train young agricultural economics researchers in Open Science, ranging from bachelor, master, doctoral to post-doctoral levels, based on the foundations in books and papers laid out by neighbouring disciplines (e.g. psychology and economics) (Christensen et al. 2019; Josephson and Michler 2024). However, experienced researchers are also in need to learn and develop in this field. Our associations (European Association of Agricultural Economists (EAAE, Agricultural and Applied Economics Association (AAEA), Agricultural Economics Society (AES), International Association of Agricultural Economists (IAAE), and many more) can play a vital role by promoting Open Science development and education in their meetings and beyond, and by leveraging their power in communication, publishing, and education. For example, initiatives such as the gold open access journal *Applied Economics Teaching Resources* (https://www.aetrjournal.org/) could play a role in pushing for more open educational resources as it publishes papers that ‘support and advance teaching and extension education within the scholarly areas of agricultural and applied economics, and agribusiness economics and management’ (https://www.aetrjournal.org/contribute/submission-guidelines).

To scale-up Open Science in agricultural economics, a shift of the entire discipline is required, involving all actors, such as researchers and universities but also associations, journals, funding agencies, and policymakers. Our journals, for example, can clarify and increase their expectations about the Open Science practices required in the entire research and publication process. By aligning these steps across journals in our discipline, the costs for authors would decrease and benefits for our profession at large could be created. Universities could create an environment to promote Open Science, e.g. in teaching, providing support, and technical platforms (e.g. for data storage and sharing) and by creating incentive structures (e.g. acknowledging Open Science as an important element in hiring and promotion decisions). The increased engagement in Open Science in agricultural economics would also be of benefit for agricultural and food policymakers. For example, by increasing reliability and reusability of scientific work (Finger, Grebitus, and Henningsen 2024), policymakers can promote Open Science by requesting policy-related work (also outside of universities) to apply Open Science practices and by supporting a beneficial environment for Open Science. Finally, funding agencies will play a vital role to develop Open Science practices—for example, by financing specific research (e.g. replication studies), supporting tools and infrastructure, and by requesting ambitious Open Science standards for funded projects. To conclude, while Open Science offers a host of benefits, the costs for the individual are high and a shift in the profession will be necessary to evoke change.

Acknowledgements

The authors thank Iain Fraser and an anonymous reviewer for helpful feedback, and participants of the organized session on ‘Open Science and Implications for the Agricultural Economics Profession’ at the XVII EAAE Congress, 31 August 2023, for useful input and discussions. We thank Silke Hüttel for feedback and suggestions regarding open educational resources and Carl-Emil Pless for feedback and suggestions regarding Replication Packages.

End Notes

1 Note that Open Science may interfere with questions of intellectual property rights but potential areas of tension can be addressed in holistic policy approaches (see Cueva and Mendez 2022).

2 Note that widely used software (e.g. Stata, Limdep/NLOGIT, SAS, or SPSS) is not free, i.e. the software needed to use openly available code is proprietary and, thus, code for these software packages could be of limited use for those who cannot afford the software. While this is not fully in line with Open Science, code shall still be made available so it is possible to replicate if the replicating researcher has access to the software.

3 Generic statements, such as that ‘data are available upon reasonable request’, are often equivalent to not sharing data at all. Many have experienced that authors who made these statements cannot be reached, do not react to requests, or decline requests (e.g. claiming that the data got lost due to a hardware failure). Furthermore, it is inefficient to demand from colleagues who want to build on data

for an individual participant data meta-analysis to contact all authors (Krawczyk and Reuben 2012; Tedersoo et al. 2021; Garcia, McCallum, and Finger 2024). If access to datasets has to be restricted (e.g. conditional to signing data processing agreements to ensure confidentiality), the data should be stored and managed by the author's institution rather than by the individual researcher to ensure that the dataset remains accessible even if the author leaves the institution or becomes otherwise unavailable.

4 Hüttel and Hess (2024), published in the same Special Issue as this article, discuss Open Educational Resources particularly regarding artificial intelligence (AI) and research methods. An example of a widely used Open Educational Resource in the field of agricultural economics is the 'Introduction to Econometric Production Analysis with R' (Henningsen 2024).

5 In some instances, demonstrating concepts using synthetic data can be a viable alternative (Wimmer and Finger 2023).

6 Note that there are various opportunities for authors to make their code more easily findable, e.g. by publishing it in repositories such GitHub or CRAN, and/or publishing documentation of the code in a journal article that refers to the software package (e.g. in *The Stata Journal*, *The R Journal*, and *Journal of Statistical Software*).

7 It is also important to note that while individuals may benefit from open access publishing, the increase in available research in general (not only related to Open Science) means that individual researchers face an increased workload. They must spend more time writing, reviewing, and editing to keep up with the growing body of literature (Hanson et al. 2023).

8 These ten are *American Journal of Agricultural Economics*, *Applied Economic Perspectives and Policy*, *Australian Journal of Agricultural and Resource Economics*, *Canadian Journal of Agricultural Economics*, *European Review of Agricultural Economics*, *Journal of Agricultural and Resource Economics*, *Journal of Agricultural Economics*, *Agribusiness*, *Agricultural Economics*, and *Food Policy*.

9 In addition to the eight criteria of Nosek et al. (2015), the TOP factor rubric covers open science badges and registered reports.

10 PRISMA stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses; and CONSORT for Consolidated Standards of Reporting Trials.

11 Model documentations: MP-MAS: https://mp-mas.uni-hohenheim.de, AgriPoliS: https://www.agripolis.org/, and FARMIND: https://aecp.ethz.ch/research/farmind.html

12 https://www.openmodelingfoundation.org/

13 Many agricultural economists use closed-source software, e.g. Stata, Limdep/NLOGIT, or SPSS. As even publicly available code of a closed-source software is not fully in line with open code principles, we encourage researchers to use code of open-source software in their replication packages.

14 A publication of the data in addition to the replication document further increases the trust in the research because, in principle, the replication document (e.g. HTML or PDF file) could be manipulated or even fabricated and this fraud might not be detectable without access to the raw data. However, even with access to the data, fraud could happen as also (raw) datasets could be manipulated or fabricated.

15 https://github.com/sagebiej/rightseeds_dce

Appendix 1. TOP factor rubric.

	0	1	2	3
Data citation	No mention of data citation.	Journal describes citation of data in guidelines to authors with clear rules and examples.	Article requires appropriate citation for data and materials used consistent with the journal's author guidelines.	Article is not published until providing appropriate citation for data and materials following journal's author guidelines.
Details	This section refers to already existing datasets. Rationale is to incentivize publishing of them and to treat them as citable contributions to scholarship.	'All data, program code and other methods should be appropriately cited. Such materials should be recognized as original intellectual contributions and afforded recognition through citation.'	'All data, program code and other methods **must** be appropriately cited.'	**'Articles will not be published until the citations conform to these standards.'**
Data transparency	Data sharing is encouraged, or not mentioned.	Articles must state whether or not data are available.	Articles must have publicly available data, or an explanation why ethical or legal constraints prevent it.	Articles must have publicly available data and must be used to computationally reproduce or confirm results prior to publication.

Appendix 1. Continued

	0	1	2	3
Details	Level 0 applies if the journal policy does not cover all of the underlying data reported in an article.	Requiring a data availability statement satisfies this level.	If the journal only requires some data to be preserved, e.g. proteomics, then this level is not reached. If the article must include an availability statement for all other data, then Level 1 is reached, else Level 0. If the policy strongly encourages data sharing, this level is not reached. Policies that require sharing with editors and reviewers only do not apply. Policies that require sharing only 'upon request' do not apply. Words such as 'should' or 'expect' may be ambiguous. Typically, 'should' implies an encouragement and not a requirement. 'Expects' suggests a requirement, but clarification may be needed.	Policy must cover transparency and sharing requirements of Level 2, plus include a computational reproducibility step.
Analytical code transparency	Code sharing is encouraged, or not mentioned.	Articles must state whether or not code is available. Requiring a code availability statement satisfies this level	Articles must have publicly available code, or an explanation why ethical or legal constraints prevent it.	Articles must have publicly available code and must be used to computationally reproduce or confirm results prior to publication.

Appendix 1. Continued

	0	1	2	3
Details	Rationale and levels mirror 'Data transparency' above. 'Code' refers to analytical details of the study. 'Code' requirement could be satisfied if field/authors do not use code, but if the journal explicitly mentions analytical steps. Mentions of 'software' do not satisfy this requirement if it applies to software built by the authors for some other reason than analysing data. In that case, it is actually 'Materials', as described below.			
Materials transparency	Materials sharing is encouraged, or not mentioned.	Articles must state whether or not materials are available. Requiring a materials availability statement satisfies this level.	Articles must have publicly available materials, or an explanation why ethical or legal constraints prevent it.	Articles must have publicly available materials and must be used to computationally reproduce or confirm results prior to publication.
Details	Rationale and levels mirror 'Data transparency'. 'Materials' mean different things to different disciplines, particularly digital (surveys, experimental stimuli) versus physical (reagents, antibodies). Rely on discipline specific guidelines for materials *identification* when depositing physical items is not feasible.			

Appendix 1. Continued

	0	1	2	3
Reporting guidelines also known as design and analysis transparency	No mention of reporting guidelines.	Journal articulates design transparency standards.	Journal requires adherence to design transparency standards for review and publication.	Journal requires and enforces adherence to design transparency standards for review and publication.
Details	Reporting guidelines must include details of the study design. Typical examples are found on the Equator network. Guidelines or checklists for inclusion of various manuscript items (e.g. abstract, lit cited) do not count.	Standards must cover a majority of expected empirical research. If a journal recommends a reporting guideline for one minor portion of their published, empirical work, the standard is not met.		
Examples	Use of CONSORT in these guidelines does not meet standard because it does not apply to the majority of studies published.			
Study pre-registration	Journal says nothing.	Articles will state whether work was pre-registered.	Article states whether work was pre-registered and, if so, journal verifies adherence to pre-registered plan.	Journal requires that confirmatory or inferential research must be pre-registered.

Appendix 1. Continued

	0	1	2	3
Details		'Details of pre-registration should be provided with submission.' Is acceptable for disclosure.		
Analysis plan pre-registration	Journal says nothing.	Articles will state whether work was pre-registered with an analysis plan.	Article states whether work was pre-registered with an analysis plan and, if so, journal verifies adherence to pre-registered plan.	Journal requires that confirmatory or inferential research must be pre-registered with an analysis plan.
Details	Policy must explicitly mention a pre-analysis plan for credit. Otherwise the structure mirrors above standard.			
Replication studies	Journal says nothing.	Journal encourages submission of replication studies.	Journal will review replication studies blinded to results.	Registered reports for replications as a regular submission option.
Details				Level 3 is achieved only if a journal accepts replication studies.
Examples				'Pre-registered direct replications'

References

Abdulai A. and Mishra A. (2020) ‘Agricultural Economics at 50: Scholarship of the Global Agricultural Economics Community’, *Agricultural Economics*, 51: 3–15.

Aguiar A. et al. (2022) ‘The Global Trade Analysis Project (GTAP) Data Base: Version 11’, *Journal of Global Economic Analysis*, 7: 1–37.

Allaire J. et al. (2024) *Quarto (Version 1.4)*. Zenodo. https://doi.org/10.5281/zenodo.5960048

Allen C. and Mehler D. M. (2019) ‘Open Science Challenges, Benefits and Tips in Early Career and beyond’, *PLoS Biology*, 17: e3000246. ⟨https://doi.org/10.1371/journal.pbio.3000587⟩

Ankel-Peters J., Fiala N. and Neubauer F. (2023) ‘Do Economists Replicate?’ *Journal of Economic Behavior & Organization*, 212: 219–32.

—— (2024) ‘Is Economics Self-correcting? Replications in the American Economic Review’, *Economic Inquiry* [online journal], https://doi.org/10.1111/ecin.13222

Anzt H. et al. (2020) ‘An Environment for Sustainable Research Software in Germany and Beyond: Current State, Open Challenges, and Call for Action’, *F1000Research*, 9: 295.

Appel F. and Balmann A. (2023), ‘Predator or Prey? Effects of Farm Growth on Neighbouring Farms’, *Journal of Agricultural Economics*, 74: 214–36.

Armeni K. et al. (2021) ‘Towards Wide-scale Adoption of Open Science Practices: The Role of Open Science Communities’, *Science and Public Policy*, 48: 605–11.

Arpinon T. and Espinosa R. (2023). ‘A Practical Guide to Registered Reports for Economists’, *Journal of the Economic Science Association*, 9: 90–122.

Arpinon T. and Lefebvre M. (2024) ‘Registered Reports and Associated Benefits for Agricultural Economics’, *Q Open*, qoae011.

Ayllón D. et al. (2021), ‘Keeping Modelling Notebooks with TRACE: Good for You and Good for Environmental Research and Management Support’, *Environmental Modelling & Software*, 136: 104932.

Baker M. (2016) ‘Reproducibility Crisis’, *Nature*, 533: 353–66.

Barreiro-Hurlé J. (2021) ‘Spanish Journal of Agricultural Research Editorial Policy Update: Pre-registration of Submissions Based on Primary Data’, *Spanish Journal of Agricultural Research*, 19: e01105.

Berger U. et al. (2024) ‘Towards Reusable Building Blocks for Agent-Based Modelling and Theory Development’, *Environmental Modelling & Software*, 175: 106003.

Brinkman L. et al. (2021) *Open Science Monitor 2020 Utrecht University: Commissioned by the Utrecht University Open Science Programme*. Utrecht University.

Brodeur A. et al. (2024) ‘Promoting Reproducibility and Replicability in Political Science’, *Research & Politics*, 11: 20531680241233439.

Chavas J. P., Chambers R. G. and Pope R. D. (2010) ‘Production Economics and Farm Management: A Century of Contributions’, *American Journal of Agricultural Economics*, 92: 356–75.

Christensen G. et al. (2019) ‘A Study of the Impact of Data Sharing on Article Citations Using Journal Policies as a Natural Experiment’, *PLoS One*, 14: e0225883.

Christensen G., Freese J. and Miguel E. (2019) *Transparent and Reproducible Social Science Research: How to Do Open Science*. University of California Press.

Cinelli C., Forney A. and Pearl J. (2024). ‘A Crash Course in Good and Bad Controls’, *Sociological Methods & Research*, 53: 1071–1104.

Coelli T. and Henningsen A. (2020) *frontier: Stochastic Frontier Analysis*. R package version 1.1-8. ⟨https://CRAN.R-Project.org/package=frontier⟩ accessed October 2024.

Colavizza G. et al. (2020) ‘The Citation Advantage of Linking Publications to Research Data’, *PLoS One*, 15: e0230416.

Council of the European Union (2016) *The Transition towards an Open Science System*. ⟨https://data.consilium.europa.eu/doc/document/ST-9526-2016-INIT/en/pdf⟩ accessed October 2024.

Crüwell S. et al. 2019. ‘Seven Easy Steps to Open Science’, *Zeitschrift für Psychologie*, 227: 237–48.

Cueva A. J. and Mendez E. (2022) *Open Science and Intellectual Property Rights. How Can They Better Interact*. Report to the European Commission. ⟨https://openscience-ipr.eu/⟩ accessed October 2024.

Dakpo K. H. et al. (2023) *sfaR: Stochastic Frontier Analysis Routines*. R package version 1.0.0. ⟨https://CRAN.R-project.org/package=sfaR/⟩ accessed October 2024.

Dorfman J. H. et al. (2024) ‘The Future of Agricultural and Applied Economics Departments’, *Applied Economic Perspectives and Policy*, 46: 834–44.

Dreber A. and Johannesson M. (2024) 'A Framework for Evaluating Reproducibility and Replicability in Economics', *Economic Inquiry* [online journal], https://doi.org/10.1111/ecin.13244
Eisfeld-Reschke J., Herb U. and Wenzlaff K., 2014. 'Research Funding in Open Science'. In: Bartling, S., Friesike, S. (eds) *Opening Science: The Evolving Guide on How the Internet Is Changing Research, Collaboration and Scholarly Publishing*, pp. 237–53. Springer Nature.
El Benni N., Grovermann C. and Finger R. (2023) 'Towards More Evidence-Based Agricultural and Food Policies', *Q Open*, 3: qoad003.
European Commission (2016) *Guidelines on FAIR Data Management in Horizon 2020*. European Commission. Directorate-General for Research & Innovation. ⟨https://ec.europa.eu/research/participants/data/ref/h2020/grants_manual/hi/oa_pilot/h2020-hi-oa-data-mgt_en.pdf⟩ accessed October 2024.
—— (2021) *Monitoring the Open Access Policy of Horizon 2020—Final Report*. European Commission, Directorate-General for Research and Innovation. ⟨https://data.europa.eu/doi/10.2777/268348⟩ accessed January 2024.
—— (2019) *Open Science. European Commission, Directorate-General for Research and Innovation*. ⟨https://www.cesaer.org/content/10-library/2023/ec-rtd-factsheet-open-science-2019.pdf⟩ accessed January 2024.
Faul F. et al. (2007). 'G* Power 3: A Flexible Statistical Power Analysis Program for the Social, Behavioral, and Biomedical Sciences', *Behavior research methods*, 39: 175–91.
Ferraro P. J. and Shukla P. (2023) 'Credibility Crisis in Agricultural Economics', *Applied Economic Perspectives and Policy*, 45: 1275–91.
Finger R. et al. (2022) 'A Note on Performance Indicators for Agricultural Economic Journals', *Journal of Agricultural Economics*, 73: 614–20.
Finger R., Grebitus C. and Henningsen A. (2023) 'Replications in Agricultural Economics', *Applied Economic Perspectives and Policy*, 45: 1258–74.
—— (2024) 'Improving Agricultural Policy Decisions through Replications', *EuroChoices*, 23: 63–6.
Garcia V., McCallum C. and Finger R. (2024) 'Heterogeneity of European Farmers' risk Preferences: An Individual Participant Data Meta-analysis', *European Review of Agricultural Economics*, 51: 725–78.
Gaulé P. and Maystre N. (2011) 'Getting Cited: Does Open Access Help?', *Research Policy*, 40: 1332–8.
Gewin V. (2016) 'Data Sharing: An Open Mind on Open Data', *Nature*, 529: 117–9.
Gisbert-Queral M. et al. (2021a) 'Climate Impacts and Adaptation in US Dairy Systems 1981-2018', *Nature Food*, 2: 894–901.
—— (2021b) *Data and Code for Climate Impacts and Adaptation in US Dairy Systems 1981-2018. Zenodo*. https://doi.org/10.5281/zenodo.11509447
Grimm V. et al. (2006) 'A Standard Protocol for Describing Individual-Based and Agent-Based Models', *Ecological Modelling*, 198: 115–26.
—— (2014) 'Towards Better Modelling and Decision Support: Documenting Model Development, Testing, and Analysis Using TRACE', *Ecological Modelling*, 280: 129–39.
—— (2020) 'The ODD Protocol for Describing Agent-Based and Other Simulation Models: A Second Update to Improve Clarity, Replication, and Structural Realism', *Journal of Artificial Societies and Social Simulation*, 23: 7.
Hanson M. A. et al. (2023) 'The Strain on Scientific Publishing.' arXiv 2309.15884.
Heckelei T. et al. (2023) 'The p-value Debate and Statistical (Mal) Practice—Implications for the Agricultural and Food Economics Community', *German Journal of Agricultural Economics*, 72: 47–67.
Henningsen A. (2024). *Introduction to Econometric Production Analysis with R. Collection of Lecture Notes*. 6th Draft Version. Department of Food and Resource Economics, University of Copenhagen. Available at Zenodo (http://doi.org/10.5281/zenodo.11093657) and Leanpub (http://leanpub.com/ProdEconR/). accessed October 2024.
Hristov J. et al. (2020). 'Impacts of the EU's Common Agricultural Policy "Greening" Reform on Agricultural Development, Biodiversity, and Ecosystem Services', *Applied Economic Perspectives and Policy*, 42: 716–38.
Huang C. K. et al. (2024) 'Open Access Research Outputs Receive More Diverse Citations', *Scientometrics*, 129: 825–45.
Huber R. et al. (2018) 'Representation of Decision-Making in European Agricultural Agent-Based Models', *Agricultural Systems*, 167: 143–60.
Huntington-Klein N. (2021). *The effect: An Introduction to Research Design and Causality*. Chapman and Hall/CRC.

Hüttel S. and Hess S. (2024) 'Are Lessons Being Learnt from the Replication Crisis or Will the Revolution Devour Its Children? Open Q Science from the Editor's Perspective', *Q Open*, qoae019.

International Network of Open Science & Scholarship Communities (2024). *Vision and Mission*. ⟨https://osc-international.com/vision-mission/⟩ accessed June 2024.

Jacobs A. M. et al. (2020). 'Pre-Registration and Results-Free Review in Observational and Qualitative Research. The Production of Knowledge: Enhancing Progress in Social Science', 2020: 221–64. https://www.cambridge.org/core/books/abs/production-of-knowledge/preregistration-and-resultsfree-review-in-observational-and-qualitative-research/1D03594E63729777792B8ECFF134A4D8

Jetten T. H. and Spruit I. H. (2023) 'The Academic Career Framework: Good Practice WUR'. In: Chajes, C., van Rest, T., van de Worp, J., and Gorodecky, and J. (eds) *Recognition & Rewards: Embrace the Impact Recognition & Rewards Programme*. ⟨https://recognitionrewardsmagazine.nl/2023/career-paths-good-practices/#goodpractice-wur⟩ accessed October 2024.

Josephson A. and Michler J. D. (2024) *Research Ethics in Applied Economics. A Practical Guide*. Routlege.

King R. P. et al. (2010) 'Agribusiness Economics and Management', *American Journal of Agricultural Economics*, 92: 554–70.

Klein O. et al. (2018) 'A Practical Guide for Transparency in Psychological Science', *Collabra: Psychology*, 4: 20.

Kliem L. and Sagebiel J. (2023) 'Consumers' Preferences for Commons-Based and Open-Source Produce: A Discrete Choice Experiment with Directional Information Manipulations', *Food Policy*, 119: 102501.

Kluyver T. et al. (2016) 'Jupyter Notebooks—a Publishing Format for Reproducible Computational workflows.' In: Loizides, F., Schmidt (eds) *Positioning and Power in Academic Publishing: Players, Agents and Agendas*, pp. 87–90. IOS Press.

Krawczyk M. and Reuben E. (2012) '(Un)available Upon Request: Field Experiment on Researchers' Willingness to Share Supplementary Materials', *Accountability in Research*, 19: 175–86.

Langham-Putrow A., Bakker C. and Riegelman A. (2021) 'Is the Open Access Citation Advantage Real? A Systematic Review of the Citation of Open Access and Subscription-Based Articles', *PLoS One*, 16: e0253129.

Leisch F. (2002) 'Sweave, Part I: Mixing R and LaTeX: A Short Introduction to the Sweave File Format and Corresponding R Functions', *R News*, 2: 28–31.

Lybbert T. J. and Buccola S. T., 2021. 'The Evolving Ethics of Analysis, Publication, and Transparency in Applied Economics', *Applied Economic Perspectives and Policy*, 43: 1330–51.

McElreath R. (2018). Statistical rethinking: A Bayesian course with examples in R and Stan. Chapman and Hall/CRC.

Mellor D. T. et al. (2024) *TOP Factor Rubric*. ⟨https://osf.io/t2yu5⟩ accessed October 2024.

Miguel E. (2021) 'Evidence on Research Transparency in Economics', *Journal of Economic Perspectives*, 35: 193–214.

Müller B. et al. (2013), 'Describing human Decisions in Agent-Based Models—ODD + D, an Extension of the ODD Protocol', *Environmental Modelling & Software*, 48: 37–48.

Munafò M. R. et al. (2017) 'A Manifesto for Reproducible Science', *Nature Human Behaviour*, 1: 1–9.

Nosek B. A. et al. (2015) 'Promoting an Open Research Culture', *Science*, 348: 1422–5.

NSF (2023) *NSF Public Access Plan 2.0. Ensuring Open, Immediate and Equitable Access to National Science Foundation Funded Research*. National Science Foundation. ⟨https://www.nsf.gov/pubs/2023/nsf23104/nsf23104.pdf⟩ accessed November 2024.

OECD (2015) ' Making Open Science a Reality', *OECD Science, Technology and Industry Policy Papers*, No. 25, OECD Publishing, Paris. http://dx.doi.org/10.1787/5jrs2f963zs1-en

Ofosu G. K. and Posner D. N. (2023) 'Pre-analysis Plans: An Early Stocktaking', *Perspectives on Politics*, 21: 174–90.

Olken B. A. (2015) 'Promises and Perils of Pre-analysis Plans', *Journal of Economic Perspectives*, 29: 61–80.

Open Science Community Wageningen (2024) *Who Are We?* ⟨https://openscience-wageningen.com/⟩ accessed June 2024.

Park H. and Wolfram D. (2019) 'Research Software Citation in the Data Citation Index: Current Practices and Implications for Research Software Sharing and Reuse', *Journal of Informetrics*, 13: 574–82.

Pearl J. (1995). 'Causal Diagrams for Empirical Research. Biometrika', 82, 669–88. https://doi.org/10.2307/2337329

Peterson D. and Panofsky A. (2021) ‘Self-correction in Science: The Diagnostic and Integrative Motives for Replication’, *Social Studies of Science*, 51: 583–605.
Piwowar H. A., Day R. S. and Fridsma D. B. (2007) ‘Sharing Detailed Research Data Is Associated with Increased Citation Rate’, *PLoS One*, 2: e308.
Protzko J. et al. (2023) ‘High Replicability of Newly Discovered Social-Behavioural Findings Is Achievable’, *Nature Human Behaviour*, 8: 31–9.
Rosenzweig C. et al. (2013), ‘The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and Pilot Studies’, *Agricultural and Forest Meteorology*, 170: 166–82.
Schreinemachers P. and Berger T. (2011), ‘An Agent-Based Simulation Model of Human-Environment Interactions in Agricultural Systems’, *Environmental Modelling & Software*, 26: 845–59.
Schwardmann U. (2020) ‘Digital Objects—FAIR Digital Objects: Which Services Are Required?’, *Data Science Journal*, 19: 15.
Storm H., Baylis K. and Heckelei T., (2020) ‘Machine Learning in Agricultural and Applied Economics’, *European Review of Agricultural Economics*, 47: 849–92.
Sumner D. A., Alston J. M. and Glauber J. W. (2010) ‘Evolution of the Economics of Agricultural Policy’, *American Journal of Agricultural Economics*, 92: 403–23.
Tedersoo L. et al. (2021) ‘Data Sharing Practices and Data Availability Upon Request Differ across Scientific Disciplines’, *Scientific Data*, 8: 192.
Tennant J. P. et al. (2016) ‘The Academic, Economic and Societal Impacts of Open Access: An Evidence-Based Review [version 3; peer review: 4 approved, 1 approved with reservations]’, *F1000Research*, 5: 632.
Toomet O. and Henningsen A. (2008) ‘Sample Selection Models in R: Package sampleSelection’, *Journal of Statistical Software*, 27: 1–23.
Troost C. and Berger T. (2015) ‘Dealing with Uncertainty in Agent-Based Simulation: Farm-Level Modeling of Adaptation to Climate Change in Southwest Germany’, *American Journal of Agricultural Economics*, 97: 833–54.
Troost C. et al. (2023) ‘How to Keep It Adequate: A Protocol for Ensuring Validity in Agent-Based Simulation’, *Environmental Modelling & Software*, 159: 105559.
Vilhuber L. (2021) ‘AEA Data and Code Availability Policy’, *AEA Papers and Proceedings*, 111: 818–23.
—— (2023) ‘Report of the AEA Data Editor’, *AEA Papers and Proceedings*, 113: 850–63.
Wimmer S. and Finger R. (2023) ‘A Note on Synthetic Data for Replication Purposes in Agricultural Economics’, *Journal of Agricultural Economics*, 74: 316–23.
Xie Y., Allaire J. and Horner J. (2023) *markdown: Render Markdown with ‘Commonmark’*. R package version 1.12. ⟨https://CRAN.R-project.org/package=markdown⟩ accessed October 2024.
Xie Y. (2014) ‘knitr: A Comprehensive Tool for Reproducible Research in R’. In: Stodden, V., Leisch, F., and Peng, R. D.(edits) *Implementing Reproducible Computational Research*. Chapman and Hall/CRC. accessed October 2024.
—— (2015) *Dynamic Documents with R and Knitr*. 2nd edn. Chapman and Hall/CRC.
—— (2024) *knitr: A General-Purpose Package for Dynamic Report Generation in R*. R package version 1.46. ⟨https://yihui.org/knitr/⟩ accessed October 2024.
Zhang L. and Ma L. (2013) ‘Is Open Science a Double-edged Sword? Data Sharing and the Changing Citation Pattern of Chinese Economics Articles’, *Scientometrics*, 128: 2803–18.
—— (2021) ‘Does Open Data Boost Journal Impact: Evidence from Chinese Economics’, *Scientometrics*, 126: 3393–419.