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## ORIGINAL ARTICLE

# Replication code availability over time and across fields: Evidence from the German Socio-Economic Panel

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## Abstract

Providing replication code is an inexpensive way to facilitate reproducibility. However, little is known about the extent of replication code provision. Therefore, we examine the availability of replication code for over 2500 peer-reviewed articles based on the German Socio-Economic Panel (SOEP), one of the most widely used datasets in economics and other social sciences. We find that only 6% of SOEP-based studies have code available, but that this proportion has increased sharply over time. We provide evidence that the increase in code provision is driven by technological advances, individual researcher initiatives, and journal policies.

## KEYWORDS

code availability, journal policies, replication code, reproducibility, SOEP

## JEL CLASSIFICATION

A12, C80, C88

## 1 | INTRODUCTION

The reproducibility of scientific results is an essential part of the scientific method. It ensures that research can be independently verified and promotes trust in scientific results. Reproducibility is particularly important in economics because the results of economic studies are used to inform policy decisions and, hence, may have direct consequences for the lives of many individuals. A study is computationally reproducible, when other researchers, using the same data and code, get the same results as the original study (Pérignon et al., 2023). Hence, computational reproducibility depends on two crucial ingredients: the availability of data and the availability of code, that is, computer instructions in statistical software such as Stata, R, or Matlab.

The practice of making code and data available has numerous advantages for the scientific community, in addition to allowing for an easy reproduction of the published results. First, it enables others to build upon the work, fostering further investigation and a more comprehensive understanding of the subject matter. Second, errors in the code can be

**Abbreviations:** DIW, German Institute for Economic Research; JIF, journal impact factor; OSF, Open Science Framework; SOEP, German Socio-Economic Panel; TOP, Transparency and Openness Promotion.

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more easily found and corrected, strengthening the self-correction feature of the scientific system.<sup>1</sup> Third, it facilitates knowledge dissemination as others can gain deeper insights into the applied methods and coding practices from the provided code. Fourth, it might serve as a deterrent against fraud and questionable research practices like *p*-hacking, as researchers know that their code might be exposed to scrutiny. Fifth, it can serve as a signal that the researchers did not engage in questionable research practices. Sixth, while reproducibility is often seen as a rather low bar and “a minimum criterion for scientific credibility” (Fišar et al., 2024, p. 1343), it is an important basis for checking whether results are robust to alternative methods and analytical choices, and whether results can be replicated using different data. Therefore, increasing the transparency of research by making code publicly available could help overcome the current lack of such replication exercises (Ankel-Peters et al., 2023).

Despite the advantages, it is unclear to what extent economists and researchers from other social sciences make data and code available. We aim to contribute to filling this gap by examining the extent of code provision. Hence, we focus on the ingredient for reproducibility that is arguably easier to achieve: Basically, every empirical researcher can share code, but not everyone can share data, as researchers are frequently prohibited from sharing analyzed data due to legal and confidentiality reasons. This is especially relevant in economics, where secondary analysis of data collected by others, such as governmental organizations or general interest surveys, is common and only the primary data producer have the right to redistribute the data. Further, providing code is comparatively inexpensive in terms of both time and money for researchers, as it typically takes less time than sharing data.<sup>2</sup> For these reasons, we focus on a setting where data are available to researchers worldwide at no cost, making the provision of code the critical factor for reproducibility.<sup>3</sup>

To better understand the extent of code sharing and its development over time, this metascientific study focuses on code availability for publications based on one of the most widely used datasets in economics and other social sciences, the German Socio-Economic Panel (SOEP). For this purpose, we conducted an intensive search for code availability of all SOEP-based publications in peer-reviewed journals in the 1985–2021 period. We checked the journal website for each of the 2518 articles, the actual articles, the websites of 2615 distinct authors who wrote the articles, and specific online repositories. The collection of this variable is a major achievement of this paper. We use this information to address several research questions: What factors correlate with code provision? How has code provision evolved over time? Is code provision related to quality metrics, such as journal impact factors and citations? What factors drive the development of code availability over time? For the latter research question, we gathered information on journal policies on code sharing from the Transparency and Openness Promotion (TOP) framework (Nosek et al., 2015), journal websites, and a survey among editors of almost 100 journals in different disciplines.

The SOEP is particularly useful for studying code provision for several reasons. First, the SOEP data are widely used by the scientific community. The SOEP has about 3500 users worldwide (Goebel et al., 2019), and more than 2500 peer-reviewed, SOEP-based journal articles have been published. Second, the SOEP data are not only employed by economists but also by researchers from several other disciplines (in particular, sociology, psychology, political science, demography), allowing us to examine code-sharing behavior in different disciplines. Third, the SOEP group provides a list of all publications based on the SOEP data, which allows us to clearly define our target population. Fourth, the SOEP makes it possible to study developments in code provision over many years as it was established 40 years ago. Fifth, there is a clear separation of the data collector (a fieldwork agency on behalf of the SOEP group at DIW Berlin) from the data analyst. This means that the raw SOEP data can be seen as exogenous to the researchers analyzing the data and that strategic decisions in the data collection process are of little relevance. Sixth, the SOEP data can be downloaded and used free of charge by researchers around the world.<sup>4</sup> This is a major advantage of the SOEP (and similar survey data) for studies on replicability and reproducibility, in particular compared to administrative data, which often can only be analyzed in restricted access environments and often only after payment for data access.

Our empirical results show that the share of peer-reviewed SOEP studies with code available is only 6%. Examining correlates of code availability, we find that single-authored articles and articles written in languages other than English are less likely to provide code. In addition, code availability is positively correlated with higher journal impact factors and more citations. We also see that code provision is less common for studies in economics journals in our sample. When we control for year of publication, the correlations of code availability with article language and single authorship disappear, and the difference between economics and other disciplines becomes smaller, suggesting that parts of these observed correlations are driven by time effects.

We also document that the share of SOEP studies that provide code has increased sharply since the early 2010s, reaching a share of 17.8% in 2021. We argue that the increase in code provision is driven by a mix of technological advances, individual researcher awareness, and journal policies. Technological advances, including the widespread use of individual researcher websites, the establishment of journal websites, and the creation of specialized online

repositories, have reduced the financial and logistical barriers to code sharing. We also present suggestive evidence that top-down initiatives, such as journal policies on code sharing, have played an important role in increasing code availability over time. Moreover, the fact that a substantial fraction of articles only provide information about code availability on the authors' websites but not on the journal website or in the article suggests that individual researchers' awareness of the importance of code sharing also plays an important role. It also highlights the need to search the authors' websites to get a comprehensive overview of code availability.

Our study contributes to the literature on research transparency and open science practices by providing the first analysis of the development of code provision over time and across fields. We particularly contribute to two strands of literature in this field. The first is the state of data and code-sharing practices and factors that are associated with it. Previous studies show that many researchers favor data and code sharing (e.g., Baker, 2016; Christensen et al., 2020; Fecher et al., 2015; Ferguson et al., 2023). However, few researchers have actually shared data or code (Christensen et al., 2020). While most studies focus exclusively on the provision of data (e.g., Alsheikh-Ali et al., 2011; Fecher et al., 2015; Gherghina & Katsanidou, 2013; Zenk-Möltgen et al., 2018), some studies examine both data and code provision together. Colliard et al. (2023) find that less than 5% of papers published between 2010 and 2020 in one leading journal in finance, the *Journal of Financial Economics*, provide some data or code on the journal's website. Gertler et al. (2018) examine 203 empirical articles that were published in nine leading economics journals in the last three issues as of May 2016 and did not contain restricted data. They find that 72% of these articles contain the estimation code, but only 42% contain the data manipulation code that turns the raw data into the estimation data. Hardwicke et al. (2020) survey 156 empirical articles published between 2014 and 2017 across the social sciences and find that code is accessible for only one article, while Wallach et al. (2018) find that none of 104 empirical biomedical articles published between 2015 and 2017 mentioned the provision of code. Key (2016) studies the availability of data and code in empirical articles published in six leading political science journals in 2013/14. 58% of the 494 articles contain both data and code, and a further 2% of articles provide code but no data, giving a total of 60% of articles containing replication code, with considerable variation across journals. Key (2016) identifies journal policies as an important predictor of code and data availability. Gertler et al. (2018) examine the websites of 67 journals from different disciplines and find that most of the top political science and economics journals require authors to provide replication code and data before publication, while journals in sociology and psychology rarely do.

The second strand relates to the development of research transparency practices over time. Here, a general finding in the literature is that different practices of research transparency are on the rise (for an overview on the development in economics, see Miguel, 2021). For instance, in a retrospective survey, the proportion of authors who reported using open science practices (including pre-registration and public sharing of data, code, or study instruments) increased over time in both economics (Swanson et al., 2020) and other disciplines (Christensen et al., 2020; Ferguson et al., 2023). McCabe and Snyder (2014) and Mueller-Langer and Watt (2018) take advantage of the fact that some journals have switched to (hybrid) open access to study the effect of (hybrid) open access on citations. Miguel (2021) presents evidence that pre-registration and pre-analysis plans are increasingly used in experimental economics and that more and more studies register every year at the Randomized Control Trial Registry of the American Economic Association.<sup>5</sup> Moreover, more and more journals in different disciplines allow for "pre-results review," also known as "registered reports," where a research project is refereed based on its research plan and methodology before the research is conducted and results are obtained (Hardwicke & Ioannidis, 2018; Miguel, 2021).

Further, journals have implemented various policies to foster research transparency. For instance, several journals introduced editorial statements underscoring the importance of disseminating findings with non-significant or null results, and there is some evidence that these statements increased the share of results that are not statistically significant (Blanco-Perez & Brodeur, 2020). Additionally, many journals implemented explicit code and data sharing policies, and several studies highlight the importance of journal policies for data and code provision as well as for reproducibility (Christensen et al., 2019; Fišar et al., 2024; Gherghina & Katsanidou, 2013; Mueller-Langer et al., 2019; Zenk-Möltgen et al., 2018). For these reasons, we put a special emphasis on journals' code-sharing policies in our empirical analyses.

Our study contributes to the previous literature by focusing specifically on code provision. While several studies look at data sharing, it is also important to study code sharing, the other facilitator of reproducibility, as every empirical researcher can share code but not necessarily data. Our focus on publications based on the same freely available data allows us to compare code availability across fields without the distortions that arise when the use of proprietary datasets varies across fields, and when code sharing behavior is influenced by the ability to share the data. In comparison, the existing literature primarily examines the availability of data and code within a selection of journals in a specific field (Brodeur, Cook, & Neisser, 2024; Colliard et al., 2023; Key, 2016; Rainey et al., 2024; Wallach et al., 2018).

We also contribute by applying a broader search approach as we do not only look at the journal websites for reproduction material but also at the authors' websites. Moreover, we examine a rather long time horizon spanning almost 40 years and focus not only on top journals but consider a much broader range of journals.

The manuscript is organized as follows: Section 2 describes our data and variables and presents descriptive statistics. Section 3 reports empirical results on the state of replication code availability, its correlates, and its evolution over time, as well as how code availability relates to journal impact factors and article citations. Section 4 concludes and provides an outlook for future research.

## 2 | DATA

### 2.1 | Basic data: SOEP and SOEPlit

The German SOEP is one of the largest and longest-running household panel surveys in the world: The first interviews were conducted about 40 years ago (in 1984), and currently, about 30,000 individuals in about 15,000 households are interviewed annually. The SOEP covers a wide range of topics, including questions on employment, income, health, education, demography, income, housing, life satisfaction, attitudes, values, and personality. For all these reasons, it is not surprising that the SOEP is highly regarded by economists and researchers from other social science disciplines: SOEP has more than 3500 users worldwide, and in the last decade, more than 100 peer-reviewed articles have been published each year using SOEP data - and between 250 and 300 other publications (including working papers, books, policy reports, etc.) (Goebel et al., 2019).

The SOEP group at the German Institute for Economic Research (DIW Berlin) maintains a database that aims to cover all publications based on SOEP data. This database, SOEPlit (2022), is our main dataset. It contains bibliographic information about each publication, including title, type of publication, year of publication, language, journal (if applicable), digital object identifier (DOI, if available), and the names of the authors. Our version of SOEPlit is from June 2022, and we consider SOEP-based publications up to the year 2021. We focus our analyses on peer-reviewed articles published in journals listed in one of the Clarivate Analytics citation indices, that is, the Science Citation Index, the Social Science Citation Index, the Arts and Humanities Citation Index, and the Emerging Sources Citation Index.<sup>6</sup> We do not include working papers for two reasons. First, we want to avoid double counting since many working papers end up as peer-reviewed articles. Second, authors may be more reluctant to share working paper code for fear of intellectual property theft. In total, our database consists of 2518 distinct peer-reviewed publications.

### 2.2 | Data on code availability

We then checked each publication for publicly available replication code. This was done in four different ways: (i) we examined the journal webpage of each article for code availability; (ii) We reviewed all 2518 articles for references to publicly available code<sup>7</sup>; (iii) We searched the authors' webpages for code availability<sup>8</sup>; (iv) We searched specific online repositories for code availability.<sup>9</sup> If code was available, we verified that the code is accessible by downloading and opening it. Our research focuses on code that is publicly available. We did not contact the authors of the articles.<sup>10</sup>

### 2.3 | Additional data

We integrated additional information at the article and journal level into our dataset. Article-level information includes citations in Google Scholar, obtained through web scraping using the Python package Scholarly (Cholewiak et al., 2021).<sup>11</sup>

Journal-level information refers to journal impact factor (JIF) metrics as well as the primary discipline of the journal. We collected the 2-year and 5-year JIF metrics since 1997 from Clarivate's Master Journal List (2022). The JIF is merged by journal name and year of publication.<sup>12</sup> To assign the primary discipline of each journal, we use the classification of Science-Metrix (2024), which categorizes journals into 174 mutually exclusive subfields, nested within 20 mutually exclusive fields (Archambault et al., 2011). We have grouped the subfields into five categories: Economics, Sociology, Psychology, Other Social Sciences, and Health & Other Sciences.<sup>13</sup> Appendix Table A1 provides, for each of our five disciplinary categories, the names of the journals with the most articles in our dataset. We merged the journal information from Science-Metrix based on the International Standard Serial Number of the journal.<sup>14</sup>

## 2.4 | Information on journal policies

Additionally, we included information about journals' policies on replication code, following the classification of the TOP framework (Nosek et al., 2015). At the lowest level (Level 0), a journal either encourages code sharing or does not specifically mention it. Moving up to Level 1, a *code availability statement* is required in the article, indicating whether the code is accessible and, if so, where it can be found. At Level 2, *mandatory code sharing* is implemented, requiring the code to be posted to a trusted repository, with any exceptions to be identified when the article is submitted. The highest level (Level 3) involves a *reproducibility check*, requiring that the code be posted to a trusted repository and that reported analyses be independently reproduced before publication.

The TOP Factor Database (2023) provides the current level of replication code policy for 164 of the 478 journals (34%) in our sample.<sup>15</sup> We searched the websites of the other 315 journals for information on code-sharing policies.<sup>16</sup>

This search resulted in the *current* state of code-sharing policies (as of November 2023). However, we are particularly interested in the *historical* development of these policies. We, therefore, wrote to editors of journals with a code-sharing policy level of at least 1 (code availability statement) to ask (i) whether our assessment was correct and (ii) when this particular policy (and previous code policies) had been adopted. This included the editors of 94 journals in our SOEP-based sample. We received responses from 67 journals (71%) on the current status of the replication code policy, and 62 journals (67%) provided information on when the policy was adopted.<sup>17</sup> For the 32 journals from which we did not receive adoption dates, we tried to obtain the dates using the Wayback Machine (2024) to retrace when the policies were first on the journal's websites. In this way, we obtained dates for 27 of the 32 journals.<sup>18</sup>

## 2.5 | Descriptive statistics

Table 1 provides descriptive statistics to get a better idea of the 2518 SOEP-based articles in our dataset. Economics is the discipline with the most articles in our sample (45%), followed by sociology (16%), other social sciences (15%), health and other sciences (14%), and psychology (11%). While our dataset includes publications from 1985 to 2021, the number of SOEP-based publications per year increased strongly over time, from 12 in 1990 (of which 3 in economics) to 26 in 2000 (15 in economics), 118 in 2010 (68 in economics), and 176 in 2020 (52 in economics).

TABLE 1 Descriptive statistics.

	Mean	SD	Min	Max
Economics	0.45	0.50	0.00	1.00
Sociology	0.16	0.36	0.00	1.00
Psychology	0.11	0.31	0.00	1.00
Other social sciences	0.15	0.36	0.00	1.00
Health and other sciences	0.14	0.34	0.00	1.00
Publication year	2011.91	7.38	1985.00	2021.00
Journal impact factor (JIF)	1.86	2.20	0.04	40.14
5 Year JIF	2.60	2.58	0.09	43.77
Citation count from google scholar	106.19	242.25	0.00	4359.00
Language of article is English	0.87	0.33	0.00	1.00
Single author	0.28	0.45	0.00	1.00
Two authors	0.38	0.49	0.00	1.00
Three authors	0.21	0.41	0.00	1.00
Four or more authors	0.13	0.33	0.00	1.00

Note: The table displays mean, standard deviation, minimum and maximum for different variables in our sample of 2518 SOEP-based publications.

Source: Own calculations, based on SOEPlit (2022), Google Scholar (2023), and journal impact factors from Master Journal List (2022).



While the average journal impact factor is 1.86 (2.60 for the 5-year impact factor), this is a highly skewed variable with a maximum of 40 overall (*Nature* in 2016) and a maximum of 9.6 in economics (*Journal of Political Economy* in 2021). Another skewed variable is the number of citations, which ranges from 0 to 4359, with an average of 106. Thirty articles have more than 1000 citations, while about 430 articles have less than 10 citations (including 90 with no citations). The vast majority of articles are written in English (87%). The remaining articles are written in German (319 articles; 13%) and French (2 articles; less than 1%). All economics articles in our sample are in English. About 28% are single-author articles, while most articles have two authors (38%). About 13% of the articles have four or more authors.

The 2518 articles are published in 478 different journals, comprising 153 economics journals and 325 journals from other disciplines. Three hundred twelve journals (65%) have at most two articles in our dataset, while 14% of journals contribute 10 or more articles. The 10 most frequent journals in our dataset account for 26% of the articles in our sample. Appendix Table A1 lists the journals with the most articles in our dataset. While previous literature has focused mainly on the top journals in economics, it is evident that we consider a much broader range of journals. The most common economics journal in our dataset is “Labor Economics” (79 articles), but our dataset also includes economics journals ranked higher, including 20 articles from Top-5 journals. As well as journals ranked lower. Similarly, a wide range of high to low-ranked journals is included for other disciplines. Thus, our results do not primarily speak to the situation at the top, but provide a broader view of the state of replication code availability.

### 3 | RESULTS

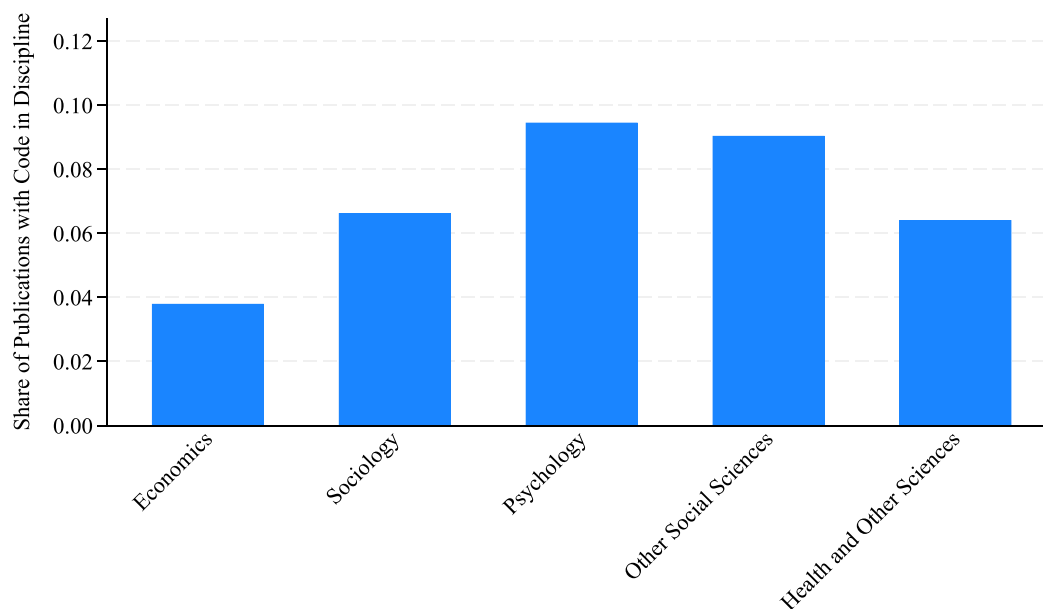
This section begins by looking at the current state of replication code availability and its correlates in Section 3.1. The following Section 3.2 describes trends in code availability over time and discusses possible explanations for the observed trends. Section 3.3 examines several factors related to code availability simultaneously, while Section 3.4 explores the relationship between code availability and quality metrics. Finally, Section 3.5 discusses results related to a more rigorous measure of code availability.

#### 3.1 | Replication code availability and its correlates

Across all disciplines, we found replication code for 151 of the 2518 SOEP-based publications (6%). Figure 1 shows the availability of code by discipline: We obtained replication code for 43 of the 1132 SOEP-based articles published in economics journals (3.8%) and for 108 of the 1386 articles published in journals of other disciplines (7.8%). The share of articles with available code is lower in economics than in the other four disciplinary categories in our SOEP-based sample. Psychology has the highest share of articles with available code (almost 10%), followed by other social sciences (9%).

We also find that articles written by a single author are less likely to contain code—and this is true in both economics and other disciplines (see Appendix Figure A1). One possible reason for this observation is that in multi-author collaborations, it is more likely that at least one author has a personal website and places importance on reproducibility. Another explanation could be that single-author articles are less likely to be published in journals with stricter code-sharing policies. A further explanation is that the importance of reproducibility becomes more apparent in multi-author collaborations. In such collaborations, ensuring that all authors obtain identical results by running the code on their respective computers becomes a more straightforward task, underscoring the importance of reproducibility. This would also align with the observation of Herbert et al. (2021) that articles with more authors tend to have better code documentation. Furthermore, code is more likely to be available if the article is written in English (see Figure A2 in the Appendix). Section 3.3 examines whether these bivariate correlations also hold when controlling for other factors, including publication year dummies and indicators for the journal’s code-sharing policy.

Next, we look more closely at the articles that provide code. The majority of articles with code provided use Stata (87%), a proprietary software, followed by R with 21% (see Appendix Figure A3).<sup>19</sup> SPSS, MATLAB, MPLUS, and SAS each account for less than 4% of studies with code. These proportions are roughly comparable to the figures from the 2018 SOEP user survey, which asked respondents about the statistical packages they use to analyze SOEP data: About 77% use Stata, 24% use R, 23% use SPSS, 11% use other (Britzke & Schupp, 2019).<sup>20</sup> Similarly, in a collection of more than 8000 economic articles with replication packages, Kranz (2023) finds that Stata is the most commonly used



**FIGURE 1** Publications with publicly available code by discipline. This figure shows the share of SOEP-based publications with publicly available replication code among all SOEP-based publications in the respective discipline. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.

software package (71.6%), followed by Matlab (24.5%) and R (9.8%). Vilhuber (2020) reports similar shares for articles in the journals of the American Economic Association.

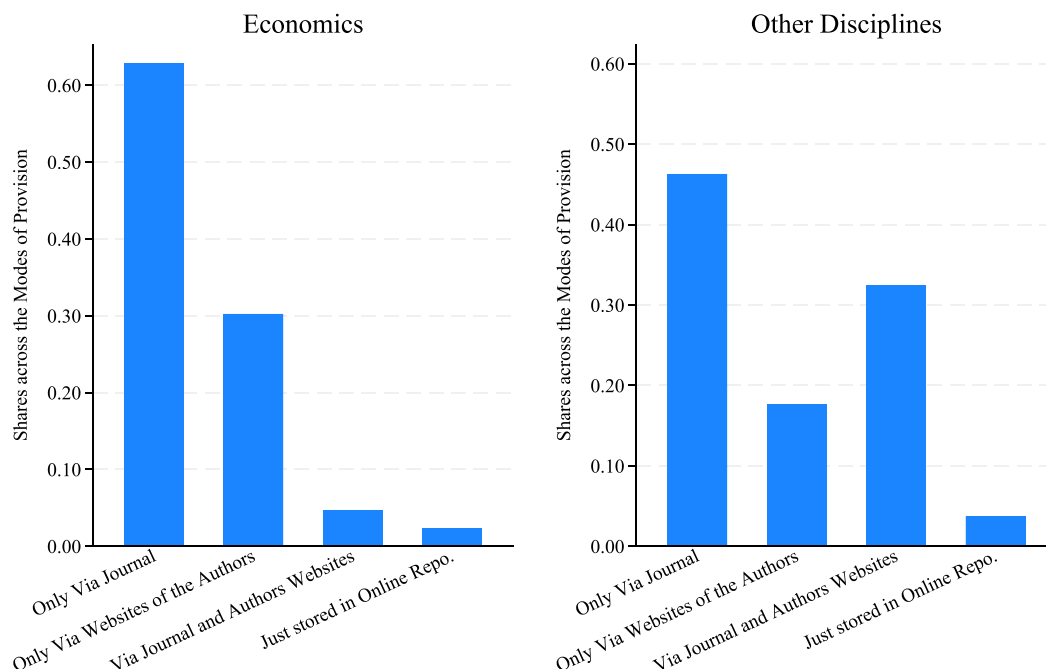
In both economics and other disciplines, most studies that provide code use the journal website to provide information about code availability (see Figure 2).<sup>21</sup> However, for a sizable proportion of studies, code availability is only disclosed via the authors' websites (30% in economics and 18% in other disciplines), highlighting the importance of also checking authors' websites for code availability: Looking only at journal websites would lead to a substantial underestimation of code availability. In general, only a few studies disseminate the code exclusively via online repositories, without referring to the availability of the code via the journal or the authors' websites (1 article in economics, 4 articles in other disciplines). It is also interesting to see that it seems less common in economics to disclose the availability of the code both through the journal and the authors' websites (5% vs. 32%). Economics also differs from other disciplines in terms of where the code provided is actually stored (see Figure A4 in the Appendix). While for the majority of studies in economics, code can be downloaded directly from author or journal websites, in other disciplines, 49% of studies with code rely on the repository of the Open Science Framework (OSF), compared to less than 5% in economics.<sup>22</sup>

### 3.2 | Developments in code availability over time

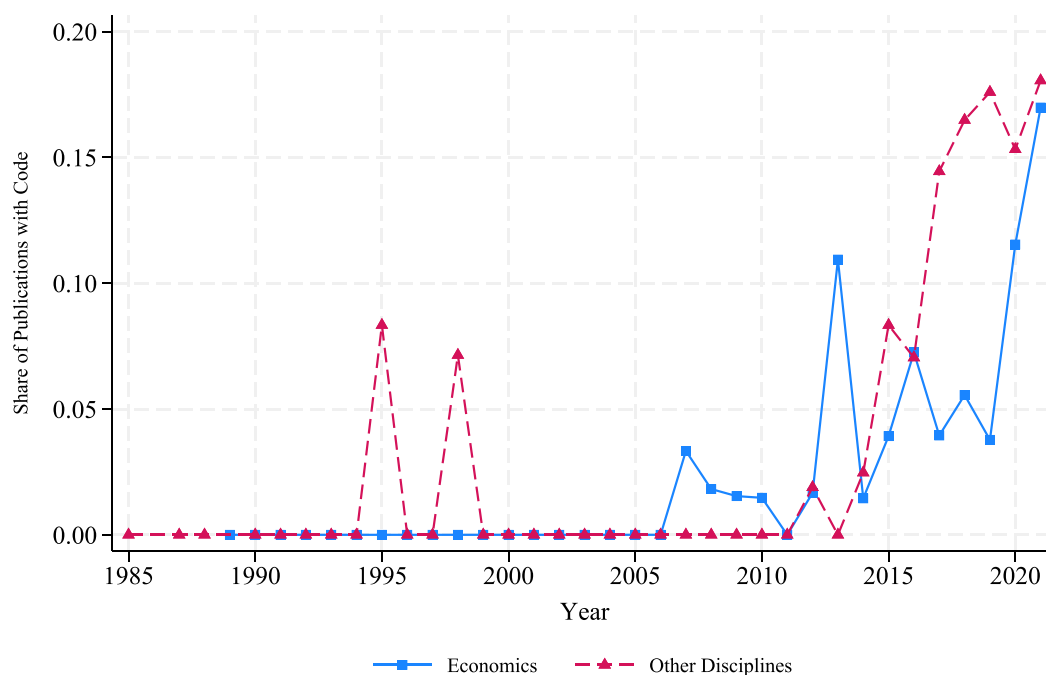
Figure 3 displays how the availability of replication code has changed over the years. It starts with the first SOEP-based peer-reviewed publications in 1985 (1989 in economics) and goes up to 2021. The figure shows several striking patterns. First, by 2012 code is available for only five studies in economics (0.85%) and three (0.55%) in other disciplines. In economics, the first publication with available code is from 2007 (Alesina & Fuchs-Schündeln, 2007), while overall, the earliest code we obtained is from 1995 (Rendtel et al., 1995). Here the SPSS code was printed as an appendix to the paper itself, highlighting the challenges researchers faced in sharing code before the widespread use of the Internet. The first digital code we found is from 1998 (Kohler, 1998). Second, the figure reveals that from 2012 onward, the annual share of publications with code increased strongly for both economics and other disciplines. The increase in economics and other disciplines from less than 2% in 2012 to 17% and 18% in 2021 suggests a huge change in code-sharing behavior. In economics, the biggest growth happened after 2019, while in the other disciplines the strongest increase occurred a few years earlier. Economics was lagging behind, but is catching up in recent years.

The breakdown of the non-economics category by discipline reveals that the increase in code provision is a general phenomenon and not driven by a single discipline (see Figure A5 in the Appendix). Until around 2015, the share of





**FIGURE 2** Publications with publicly available code by mode of disclosure. This figure displays the distribution of methods used to inform others about the availability of code among all SOEP-based publications with publicly available replication code. The left panel relates to the situation in economics, while the right panel relates to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.



**FIGURE 3** Publications with publicly available code over time. This figure shows the share of SOEP-based publications with publicly available replication code among all SOEP-based publications in the respective year and discipline. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.

publications with code was similar across disciplines. However, after 2015, the increase in sociology, psychology, and other social sciences was earlier and stronger than in economics.

Next, we look at how the mode of code availability disclosure and the location of storage have changed over time. The proportion of studies we found information on code availability through the journal increased strongly over the

years, both in economics and other disciplines (see Appendix Figure A6). There is also an increase in the proportion of studies for which we found information on code availability only through the authors' websites. However, this increase is less pronounced, suggesting that journals play a major role in the increase in code availability over time. While in other disciplines, there is an increase in the disclosure of code availability through both the journal and the authors' websites, there is no such development in economics. Appendix Figure A7 highlights the sharp increase in the use of OSF from 2015 onwards in other disciplines, but not in economics.<sup>23</sup>

There are several possible explanations for the remarkable increase in code availability over time. First, technological advances have reduced the financial and logistical barriers to code sharing. These developments include the widespread use of individual websites by researchers, the establishment of journal websites, and the creation of specialized online repositories.<sup>24</sup> Prior to these technological advances, code could only be stored and shared on floppy disks or by printing codes in appendices (as in Rendtel et al., 1995). The increased use of repositories to store code (Figure A15) and the substantial proportion of studies for which code is available on the authors' websites (Figure 2) speak to the importance of technological advances in increasing code sharing.

Second, evolving journal policies on code sharing may play an important role in explaining the positive trend in code availability over time. Appendix Figure A8 shows that in both economics and other disciplines, about 80% of journals in our sample have a Level-0 policy, meaning that the journal either encourages code sharing or does not mention code sharing at all. While Level-1 policies (stating whether code is available and, if so, where) are slightly less common in economics than in other disciplines, in both groups about 10% of journals require that code be deposited in a trusted repository (Level 2). However, the highest (and strictest) level is more common in economics journals. At this level, not only must the code be deposited in a trusted repository, but all article's results must be independently reproduced.

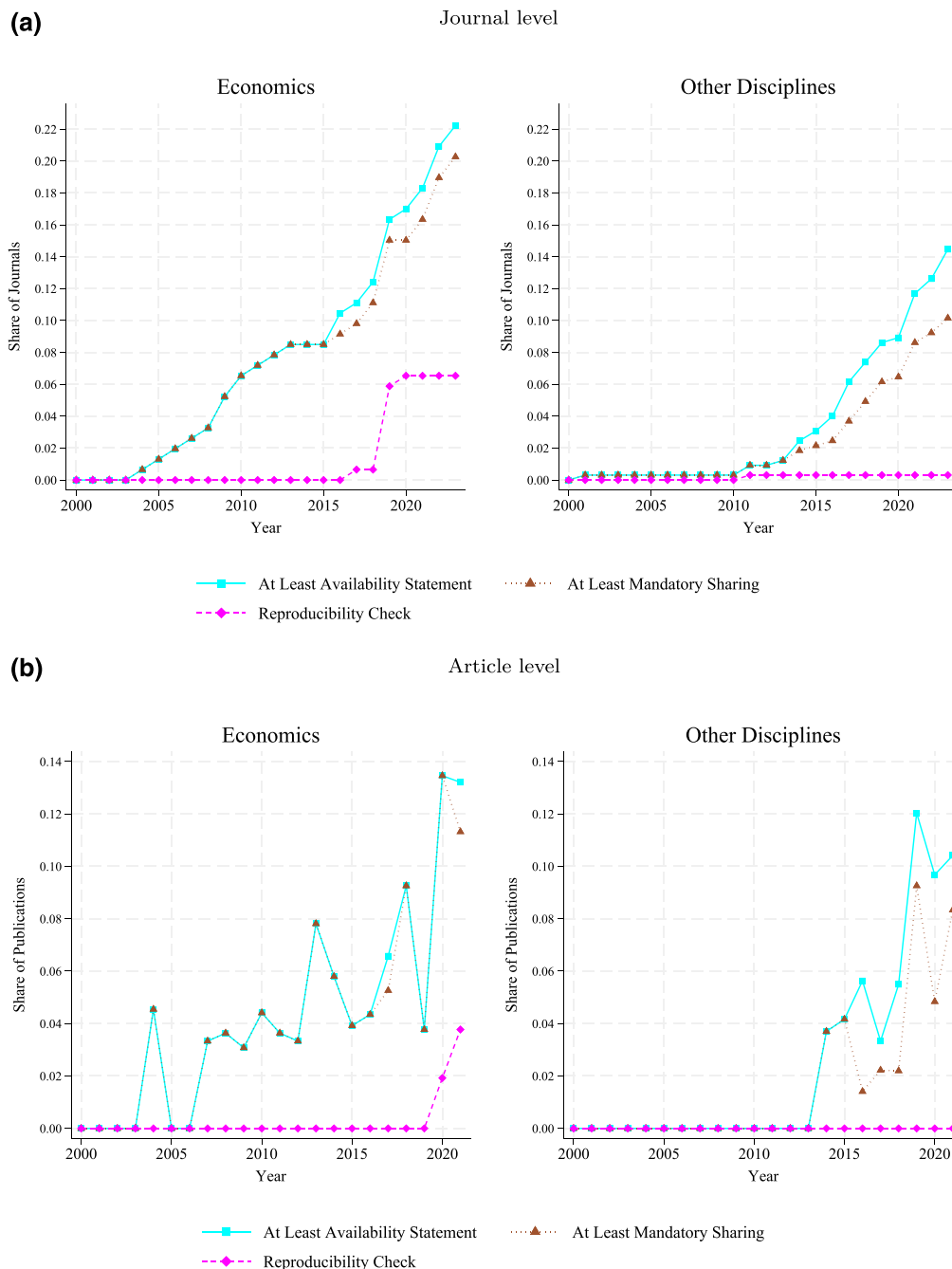
We then examine how these code-sharing policies have evolved over time for the 478 journals in our sample (see the upper panels of Figure 4). The *American Economic Review* was the first economics journal in our dataset to announce an explicit code-sharing policy (Bernanke, 2004).<sup>25</sup> In economics, the share of journals requiring mandatory code sharing has increased continuously since 2004, with a particularly strong increase in the period 2015–2019. By 2021, more than 20% of the economics journals in our sample (31 out of 153) have a mandatory code-sharing policy. In other disciplines, there has also been a notable increase in Level-2 policies, which kicked in somewhat later.<sup>26</sup> By 2021, 10% of non-economics journals require the provision of replication code. Similarly, we see that at the end of our observation period, the share of journals with reproducibility checks (Level 3) is higher in economics.<sup>27</sup>

While the upper panels of Figure 4 look at the journal level, the lower panels of this figure examine how many of the articles in our dataset were published when a code-sharing policy was in place. In our sample, the first such articles are from 2007 in economics and 2014 in other disciplines. These two dates roughly coincide with the first available replication codes (apart from the two articles with code from the 1990s), speaking to the relevance of these policies. After these dates, the share of articles covered by a mandatory code-sharing policy increased steadily, up to more than 11% in economics and more than 8% in other disciplines in 2021. Only three articles in our sample were published when a reproducibility check was in place (Level 3), all of them in economics.

The importance of journal policies for code provision is underlined by the fact that four of the five code-providing economics articles published in or before 2012 (see Figure 3) are published in journals with mandatory code-sharing policies (three in the *American Economic Review* and one in the *Review of Economic Studies*).<sup>28</sup>

Apart from technological and journal policies, a third explanation for the increase in code availability over time could be the heightened awareness among researchers, driven by, for instance, negative examples of retracted studies and the discussion about a reproducibility and replicability crisis. Romero (2019) traces the beginning of the discussion around the replicability crisis to several events in the early 2010s. This broadly coincides with the increased availability of replication code in our sample. Moreover, starting in the 2010s, several comprehensive studies documented that many published articles cannot be replicated; this includes psychology (Open Science Collaboration, 2015), cancer research (Nosek & Errington, 2017), experiments in economics (Camerer et al., 2016) and social sciences in general (Camerer et al., 2018). This increased awareness of the replicability crisis may have contributed both to more authors sharing their code, making their studies easier to reproduce, and to more journals implementing code (and data) sharing policies. In economics, the debate centering around Herndon et al. (2013) and Reinhart and Rogoff (2010) has also contributed to a growing awareness of reproducibility and code availability (Mueller-Langer et al., 2019).

While Figure 4 suggests that journal policies have contributed to the increase in code provision over time, it is important to note that less than 5% of articles in both economics and other disciplines were published when a Level 1 or higher code-sharing policy was in place. Furthermore, Figure 5 shows that there is also an increase in code availability over time net of journal policies. This figure excludes publications published when the journal had a code-sharing

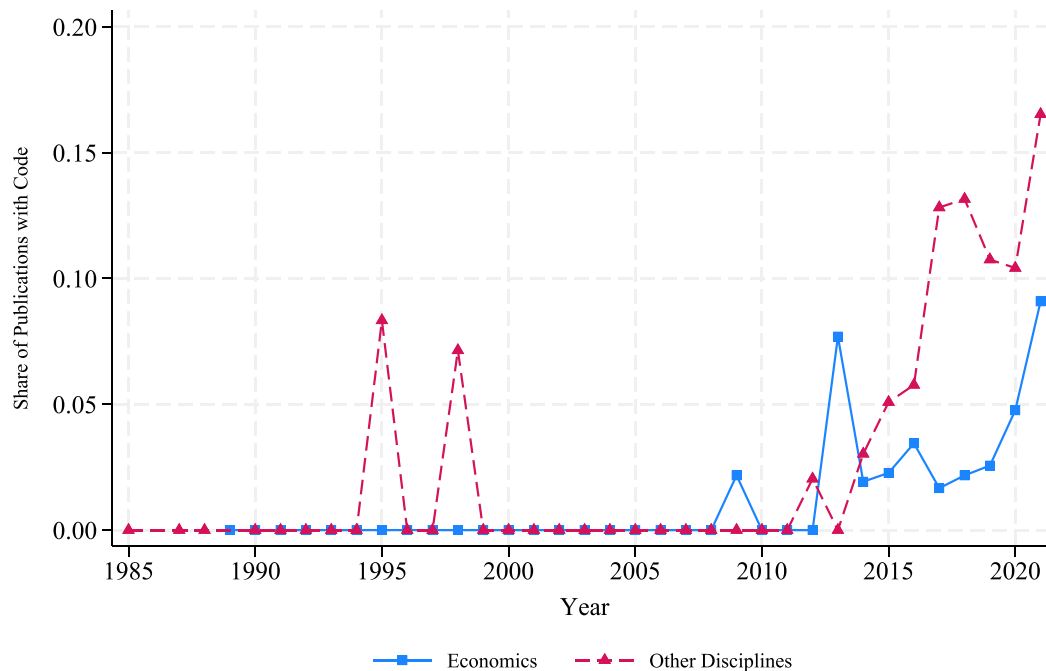


**FIGURE 4** Development of code sharing policies over time. (a) Journal level. (b) Article level. This figure shows the development of replication code policies over time for the journal (upper panels) and articles (lower panels) in our sample. The left panels relate to the situation in economics, while the right panels relate to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022), TOP Factor Database (2023), and own research on journals' replication code policies.

policy of Level 1 or higher.<sup>29</sup> We take this as indirect evidence that bottom-up initiatives by individual researchers to make their code available, even when not required by the journal, have also contributed to the increase in code availability.

### 3.3 | Regression results: Predictors of code availability

In this section, we use regression analysis to examine several factors related to code availability simultaneously. More specifically, we estimate linear probability models with code availability as the binary dependent variable, in which we



**FIGURE 5** Publicly available code, net of journal policies. This figure shows the share of SOEP-based publications with publicly available replication code among all SOEP-based publications in the respective year and discipline, excluding publications that were published when the journal had a code-sharing policy in place. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.

sequentially include the previously discussed factors.<sup>30</sup> Table 2 shows the results. The first column of this table is based on the bivariate associations from Figure 1 between code availability and disciplines. Economics is the reference category, and it can be seen that the coefficients for all four other disciplines are positive, indicating that among SOEP-based articles, code provision is less common in economics. The coefficients for all four disciplines are reduced when publication year dummies are included in column (2). This suggests that the lower prevalence of code-sharing in economics is partly due to the higher proportion of economics articles in publications from earlier years when code-sharing was generally less prevalent. While all four discipline coefficients are smaller in column (2), the coefficients are still jointly statistically significant.

This picture remains the same when including indicator variables for whether the article is in English and whether the article was written by a single author (column 3). While the bivariate associations showed that code provision is generally higher among English articles (see Figure A2), this association disappears when publication year dummies are included. This indicates that the lower share of articles in other languages with provided code is due to the fact that non-English articles were mostly published in earlier years when code provision was less common. Similarly, the negative correlation between single authorship and the likelihood of providing code is considerably reduced and no longer statistically significant at the 5% level, when controlling for discipline, year of publication, and article language.

Column (4) considers journal policies on code sharing, with a Level-0 policy as the reference category. The coefficients for Level 2 (Mandatory Code Sharing), and Level 3 (Reproducibility Check) are positive and significant, indicating that they are positively related to code sharing compared to a policy that says nothing about code sharing or only encourages it. The coefficients for Level 2 and Level 3 are large relative to all other coefficients in the table, suggesting that a mandatory code-sharing policy (which is also part of Level 3) greatly increases the availability of code. The coefficient for Level 2 suggests that a mandatory code-sharing policy is associated with an increase in code availability of more than 36% points. While this is a considerable magnitude, it is also not close to 100. This is consistent with previous findings in the literature that mandatory code policies are not always strictly enforced (Colliard et al., 2023; Vlaeminck & Herrmann, 2015). Interestingly, the coefficients for the other disciplines increase when controlling for journal policies on code sharing. This suggests that code sharing is lower in economics despite the stricter code-sharing policies.

TABLE 2 Predictors of code availability.

	Dependent variable: Code available (Yes/No)				
	(1)	(2)	(3)	(4)	(5)
Sociology	0.028*	0.025	0.027	0.043**	0.046**
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Psychology	0.057**	0.027	0.026	0.027	0.005
	(0.019)	(0.018)	(0.018)	(0.017)	(0.017)
Other social sciences	0.052***	0.029	0.030	0.040**	0.040**
	(0.016)	(0.015)	(0.016)	(0.014)	(0.015)
Health and other sciences	0.026	0.000	−0.001	−0.003	0.004
	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)
English article			0.000	−0.002	−0.002
			(0.014)	(0.014)	(0.014)
Single author			−0.018	−0.011	−0.012
			(0.009)	(0.009)	(0.009)
Code availability statement				0.044	
				(0.076)	
Mandatory code sharing				0.366***	
				(0.053)	
Reproducibility check				0.556*	
				(0.280)	
Publication year FE	No	Yes	Yes	Yes	Yes
Only Level-0 journals	No	No	No	No	Yes
F (4, N−1)	5.18***	1.96***	1.96***	4.35***	3.92***
Adj. R <sup>2</sup>	0.01	0.05	0.05	0.14	0.04
N	2518	2518	2518	2450	2057

Note: The table shows coefficients for linear probability models with code availability as binary dependent variable and robust standard errors in parentheses. The base categories for the discipline dummies is economics. The F-statistic in the bottom row refers to an F-test that the four disciplinary indicators are jointly zero.

\* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ .

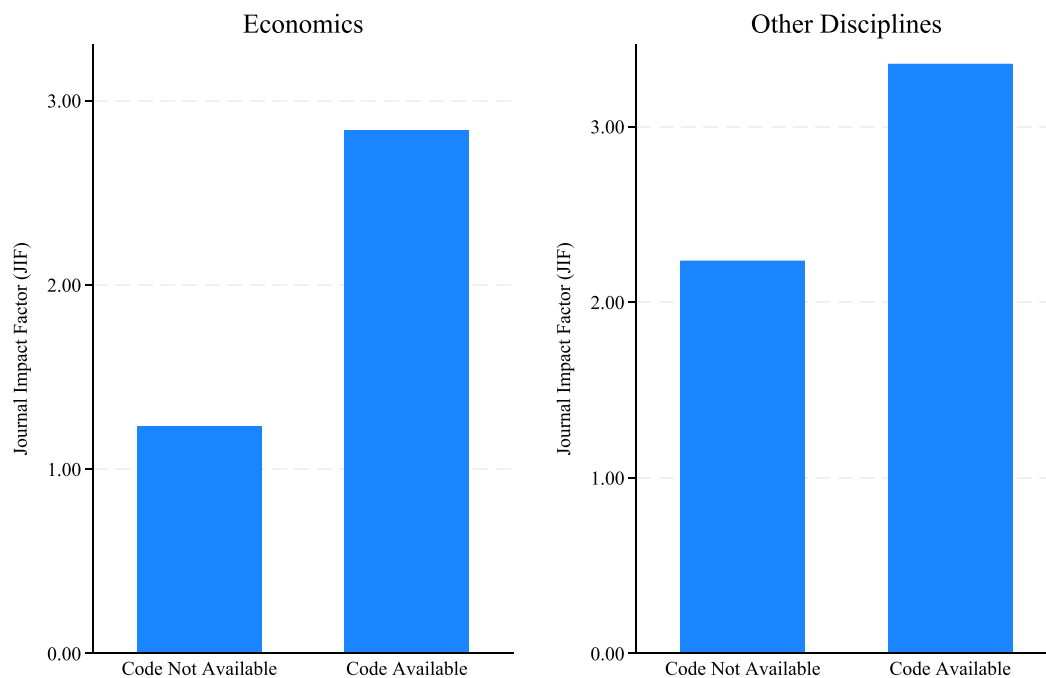
Source: Own calculations, based on SOEPlit (2022) as well as own research on code availability and journals' replication code policies.

### 3.4 | Code availability and quality metrics

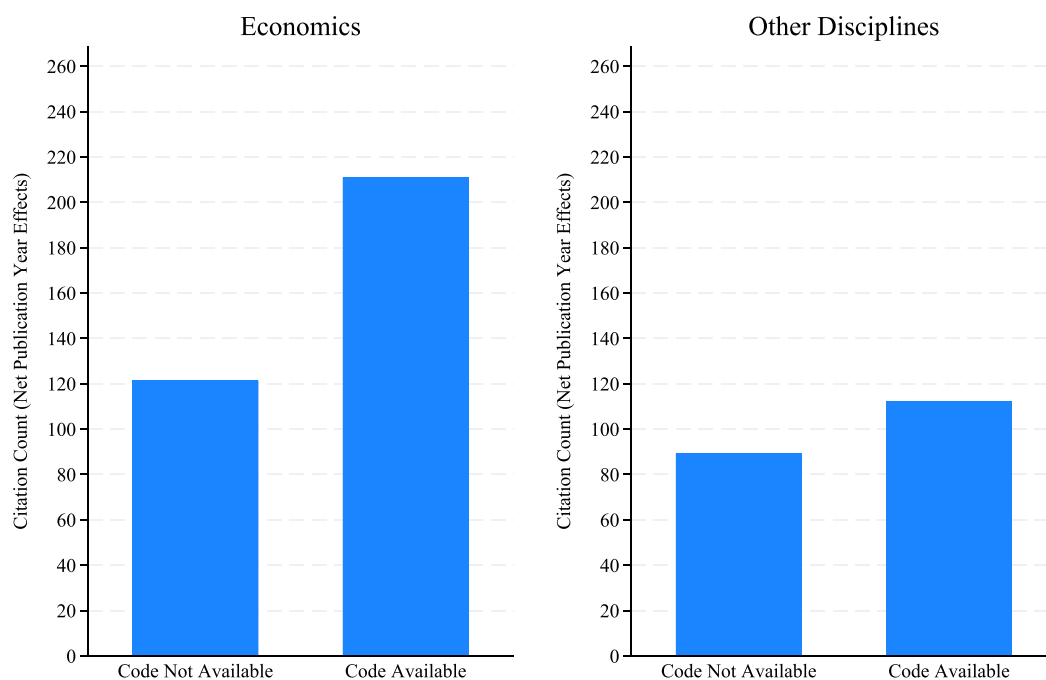
The left panel of Figure 6 shows that the average journal impact factor for SOEP-based publications in economics is about 2 for articles that provide code, while it is about 1.3 for articles that do not provide code. The picture is very similar when looking at all other disciplines (right panel of Figure 6) or when looking at 5-year impact factors (see Appendix Figure A9): Code-sharing is correlated with higher impact factors. Multiple regression analyses, presented in Appendix Table A2, confirm this finding. The regression results show that, code availability is associated with a 0.94 point higher JIF in economics and a 0.51 point higher JIF in other disciplines, controlling for year fixed effects. This relationship does not change much when controlling for the single-author indicator, the language of the article, and the journal's code-sharing policy. Code sharing is correlated with higher impact factors - and we cannot explain this correlation with the included predictor variables.

Figure 7 shows the average number of citations in Google Scholar for studies with and without available code.<sup>31</sup> It shows that in both economics and other disciplines, articles with replication code available receive, on average, more citations than articles without code. This relationship is more pronounced in economics than in other disciplines.





**FIGURE 6** Code availability and journal impact factor. This figure shows the average journal impact factor separately for SOEP-publications with and without provided code. The left panel relates to publications in economics, while the right panel relates to publications in all other disciplines. *Source:* Own calculations, based on SOEPlit (2022), journal impact factors from Master Journal List (2022), and own research on code availability.



**FIGURE 7** Code availability and citations. This figure shows the average citations in Google Scholar for SOEP-publications with and without provided code. The left panel relates to publications in economics, while the right panel relates to publications in all other disciplines. The displayed numbers in this figure are net of publication year dummies. *Source:* Own calculations, based on SOEPlit (2022), Google Scholar (2023), and own research on code availability.

Table A3 in the Appendix shows average marginal effects from related Poisson regressions. The table confirms that articles with available code receive more citations, also when controlling for the single author indicator and the language of the article: Articles with available code receive on average 182 more citations in economics and 46 more in

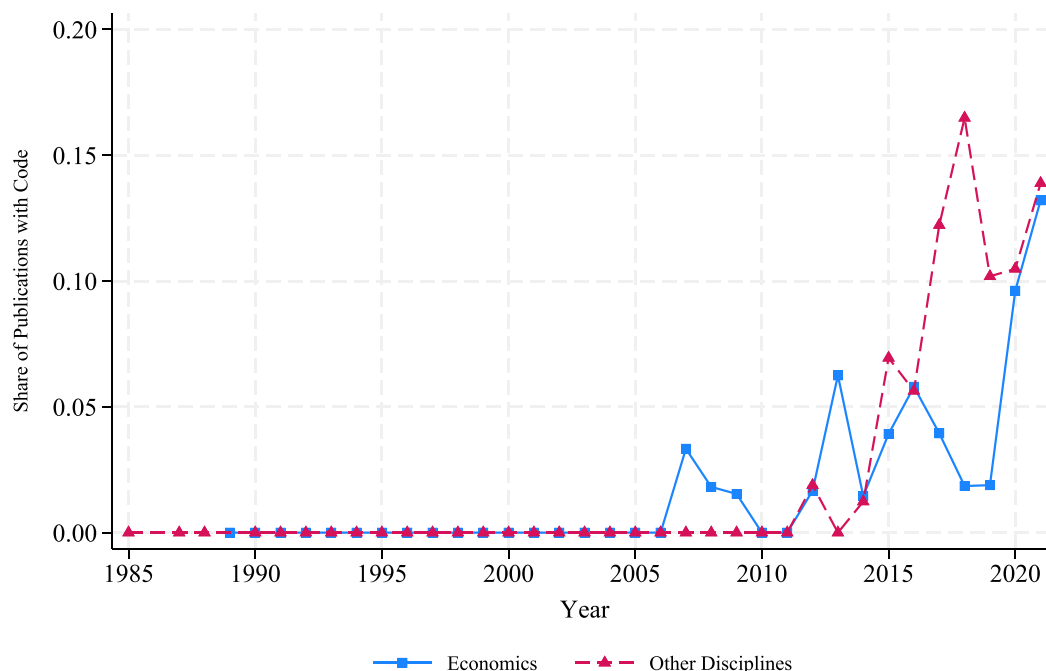
other disciplines. However, these associations should not be interpreted as causal effects of code availability, as we have not accounted for article quality and other potential confounding factors. This point is reinforced by the fact that, once we control for journal policies and impact factors (which serve as proxies for article quality), the coefficients for code availability drop significantly in size and lose statistical significance.

### 3.5 | Robustness

While in the previous sections, we focused on whether any replication code was available, we did not consider the quality of the code provided in terms of its ability to reproduce the results. The quality of code is important as several studies have shown that code availability does not ensure computational reproducibility (see e.g. Chang & Li, 2017; Eubank, 2016; Fišar et al., 2024; Gertler et al., 2018; Herbert et al., 2021; McCullough et al., 2006; Pérignon et al., 2023), mostly due to missing data, non-transferability of code from one computer to the replicator's computer, unstable results after repeated code runs, and differences between published and reproduced results (including copying errors). However, it is beyond the scope of this paper to analyze the reproducibility of all 151 SOEP papers with code provided. For example, Gertler et al. (2018) report that in their attempt to reproduce the results of published papers in economics, they set a limit of 4 hours for each paper to try to run the code (excluding code runtime).

As a first step in looking at the quality of the code provided, we work with a stricter definition of code availability. More specifically, we count a publication as providing code only if the code loads raw SOEP data, which means that replication packages that do not start with the raw SOEP data (as provided by the SOEP group) but with some intermediate “analysis” dataset are not counted. Likely, such an intermediate dataset will not allow the exact reproduction of the final results since many hidden researcher decisions relate to sample restriction and variable definition choices.

We find that about a quarter of the publications that provide some code do not start from the raw SOEP data, but from some intermediate dataset. This means that using the stricter measure of replication code availability, only 4.5% of the publications in our dataset provide code, or 113 in absolute terms. Figure 8 shows the evolution of code availability (according to the stricter definition) over time. Comparing this figure to Figure 3, which is based on our main definition of code availability, several observations stand out. First, the overall pattern is the same: code availability increases over time in both economics and other disciplines. Second, the first study with available code that loads the SOEP raw data is



**FIGURE 8** Publicly available code that loads raw Socio-Economic Panel (SOEP) data over time. This figure shows the share of SOEP-based publications with publicly available replication code that loads raw SOEP data among all SOEP-based publications in the respective year and discipline. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.

from 2007 (12 years later than the first publication with any replication code), and the first publication outside of economics that provides code according to the stricter definition is from 2012 (Kohler et al., 2012).

While none of the studies providing code met the stricter definition in the period before 2007, the proportion of studies with code meeting the stricter definition remained relatively constant over time (75% in 2007–2011%, 76.7% in 2012–2016%, 75.7% in 2017–2021). This suggests that code quality, as measured by our crude measure, has not improved much over time. However, it also suggests that the increased rate of code provision over time did not come at the expense of the quality of the code provided. The Online Appendix repeats all our analyses, this time using the stricter definition of code availability. Generally, the patterns are very similar to those with our main definition of code availability.

## 4 | CONCLUSION

In his famous article “Let’s take the con out of econometrics” Edward Leamer (1983) heavily criticized the state of empirical economic research, culminating in the quote “hardly anyone takes anyone else’s data analysis seriously.” If nobody takes data analysis of other researcher serious, it is a serious problem for a profession that strongly relies on empirical results and calls for evidence-based policy-making. However, Angrist and Pischke (2010) argue that the Leamer critique is no longer justified in empirical microeconomics due to the commitment to rigorous research designs for identifying causal effects. This is what they label the credibility revolution in their aptly titled article “The credibility revolution in empirical economics: How better research design is taking the con out of econometrics.” However, recent studies by, for example, Huntington-Klein et al. (2021), Breznau et al. (2022), and Menkveld et al. (2024) highlight a disconcerting phenomenon: researchers drawing disparate conclusions when analyzing the same data to answer identical questions, even when they apply rigorous research designs for the identification of causal effects. This is due to the many decisions that researchers must make during data collection, preparation, and analysis, also known as the researcher’s degree of freedom. It suggests that relying solely on credible research designs does not fully address the lingering concerns voiced by Leamer (1983). Making data and code used in the empirical analysis publicly available is one way to make the researcher’s degree of freedom more transparent and to examine how crucial it is for a given research question. Having access to data and code would allow others to check all the details of the empirical analyses and run additional sensitivity checks.

Against this backdrop, this study looks at how often researchers share the computer code they use for their empirical analyses, focusing on publications that use the SOEP dataset—a widely-used data source in economics and other disciplines. We searched extensively to find out if the code was available for all 2518 articles using SOEP in peer-reviewed journals. We checked the journal websites, the articles themselves, the websites of the authors, and specific online repositories.

The analysis shows that only 6% of SOEP studies have accessible replication code, a low proportion, particularly considering that code provision is crucial for the reproducibility of scientific results and associated with little costs for the researchers. However, there is a positive trend as the share of studies with available code increased strongly over time in both economics and other disciplines. We argue that this increase is driven by a mixture of three factors: Technological advances (including websites of authors and journals as well as the establishment of specific repositories), top-down initiatives of journals, for example, mandating code sharing, and bottom-up initiatives of individual researchers, who post code on their individual websites. Additionally, we find that studies with accessible code tend to be published in journals with higher impact factors and receive more citations, emphasizing the potential of code sharing as a quality signal in academic research.

Our analysis can serve as a first step for further analyses. We sketch five of such further analyses. First, we examine whether studies provide replication code, but we do not study whether the code actually allowed the results to be reproduced. We take a first step in this direction, by applying the stricter definition of code availability where the code must load raw SOEP data. However, it is beyond the scope of this paper to analyze the reproducibility of all SOEP papers with code provided. Second, another potential avenue for future research is to go more in the direction of causality. While we document correlations between journal policies and code availability, future research could evaluate the impact of code-sharing policies on code availability with more rigorous methods for causal inference. Similarly, future studies could look at the effects of code provision on citation metrics.<sup>32</sup> Third, while in the introduction we argue that code provision might work as a deterrent against fraud and questionable research practices like *p*-hacking, further analyses could study whether this is actually the case.<sup>33</sup> Fourth, further research could identify the specific barriers that

prevent authors from adopting the habit of making code available, and ways to overcome these barriers (e.g., journals providing assistance in the form of instructions or videos on how to prepare replication packages).

Fifth, future studies could also examine code availability beyond the SOEP. A possible approach would be to investigate the development of code availability in articles published in leading journals across various disciplines. However, this sampling method may not offer a comprehensive overview of code sharing as it concentrates solely on the most prestigious journals. Further, in many cases the provision of code will not be enough to allow for reproducibility as data are missing and there are substantial differences between disciplines regarding the proportion of data that are shareable with the research community. While publications based on the SOEP are not a random sample of studies in economics or other disciplines, a complimentary strategy would be to draw random samples from publications in different disciplines. However, this procedure presents several challenges. Firstly, it is necessary to verify whether the study is an empirical one and the rates of empirical studies differ between disciplines. Secondly, the disciplines vary in terms of the proportion of publications based on primary or secondary data analyses. Thirdly, it is unclear what the population is and how to construct a sampling frame. By focusing on the SOEP, we avoid many of these issues as the SOEP levels the playing field as the dataset is publicly available by researchers around the world. In this setting code availability is the most crucial ingredient for reproducibility.

Providing replication code will not completely solve all problems of questionable research practices and scientific malpractice. However, it will mitigate some of these problems and make it easier for new studies to build on previous ones. In addition, code provision is a relatively inexpensive measure: Individual researchers can participate voluntarily, and journals can adopt explicit code-sharing policies.

For journals, the cost of implementing a Level-1 code-sharing policy (code availability statement) is relatively low. Journals simply need to update their web pages to explicitly mention the policy and ensure that each accepted paper includes a code availability statement. The cost of implementing a Level-2 policy (mandatory code provision) is only slightly higher, as journals must enforce this policy by verifying that the code is posted in a trusted repository and that the link provided is functional. A potential downside of implementing an explicit code-sharing policy could be that fewer researchers would submit their work to such journals. However, we believe that this is unlikely because the costs to individual researchers are relatively low for both Level-1 and Level-2 policies. Moreover, if the policy deters researchers who might engage in fraudulent behavior, it could be beneficial for the journal to receive fewer but higher quality submissions. From a pure reproducibility perspective, a Level-3 policy (reproducibility check) is desirable. However, this is by far the most expensive code-sharing policy. Verifying that the code allows for reproducibility is costly, and many journals employ data editors to perform these checks, at considerable expense. In our survey, editors from several journals indicated that while they would like to implement a Level-3 policy, it is simply not financially feasible. While we believe that only select top-tier journals can afford comprehensive reproducibility checks, all journals can (and should) require authors of accepted manuscripts to make their code publicly available.

We conclude this paper by arguing for what we call the Credibility Revolution 2.0. This new paradigm contends that the mere focus on research designs is not enough to address the criticisms of Leamer (1983). Instead, it calls for a fundamental shift toward sharing code and, if possible, data as the new normal. In our view, the credibility lies not only in the design of the research, but also in the ability of peers to scrutinize every detail, facilitating collective validation of results through reproducibility and transparency. Providing replication code is a low-cost measure in this new paradigm, and basically any empirical researcher can engage in it, paving the way for more trustworthy empirical research.

## ACKNOWLEDGMENTS

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## DATA AVAILABILITY STATEMENT

The code and data to reproduce all the tables and figures in the paper are openly available in the openICPSR repository at <https://doi.org/10.3886/E209316V2> (Fink & Marcus, 2024).

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## ENDNOTES

- <sup>1</sup> For example, Foote and Goetz (2008) found a coding error in Donohue and Levitt (2001)'s study on legalized abortion and crime, while Herndon et al. (2013) found a coding error in an Excel spreadsheet in Reinhart and Rogoff (2010)'s original study on high public debt and low growth rates. Although these examples of coding errors received a lot of attention, (unintentional) coding errors often have only minor consequences for the conclusions of an article (Laurinavichyute et al., 2022).
- <sup>2</sup> For data sharing, researchers may need to label variables and carefully consider which variables should not be released. This may be to reduce the risk of de-anonymizing specific observations or because they plan to publish another paper using the same data and variables that have not been used.
- <sup>3</sup> One might consider including all details of the empirical analyses in the article as an alternative to code provision. However, journals have limited space, and even the most careful researchers find it challenging to include all the important details of their analysis in the article (Krähmer et al., 2023). Moreover, our own experience in trying to reproduce results of publications using only the provided data and information provided in the article tells us that this is not only time-consuming, but in most cases it is impossible to reproduce the results due to the complexity of most empirical analyses and the many decisions researchers have to take.
- <sup>4</sup> More specifically, researchers at universities and research institutions can use the data for research and teaching purposes by signing a data distribution contract, wherein they agree to comply with the data security and privacy requirements of the European General Data Protection Regulation. Data protection rules differ inside and outside the EU. Within the EU, users have full access to the SOEP core dataset, outside the EU, they have access to a 95% sample of this dataset. The core SOEP data contain information on the federal state. More detailed regional data are available via remote or on-site access. See SOEP Group (2024) and Vilhuber (2023) for more information.
- <sup>5</sup> The purpose of pre-registrations and pre-analysis plans is to enhance confidence in a study's findings by reducing researchers' degree of freedom and the capacity to choose results selectively. While in economics, pre-registration refers to the process of registering and describing the basic characteristics of a study (usually) before it is conducted, pre-analysis plans additionally describe in detail how the analysis will be performed (Miguel, 2021). In economics, pre-registration often comes without a pre-analysis plan, while in other disciplines, pre-registration, by definition, includes a pre-analysis plan (Brodeur, Cook, Hartley, & Heyes, 2024). The empirical study by Brodeur, Cook, Hartley, and Heyes (2024) shows that pre-registration reduces *p*-hacking and publication bias only when accompanied by a pre-analysis plan.
- <sup>6</sup> In our sample, based on the first category of Clarivate's Master Journal List, the Social Science Citation Index accounts for the majority of articles (86%), while the Science Citation Index makes up another 10%.
- <sup>7</sup> In particular, student assistants reviewed the acknowledgments and searched the paper for key terms such as "code," "replication," "syntax," "script" and "Stata."
- <sup>8</sup> More specifically, our student assistants checked the personal webpages or, if not found, the institutional webpages of the first four authors for code. This results in 2615 distinct authors. We only consider the first four authors as more than four authors are present in only 6% of studies. Among these, a few studies have a large number of authors, including three papers with close to 100 authors.
- <sup>9</sup> These include the GESIS data archive, Harvard Dataverse, Open Science Framework, openICPSR, and Zenodo. We used the search terms "SOEP," "GSOEP," "Socio-Economic Panel," and "Sozio-oekonomisches Panel."
- <sup>10</sup> Krähmer et al. (2023) took a different approach, contacting authors who had published with data from the European Social Survey and asking if they would share their code. 37.5% of successfully contacted authors provided code.
- <sup>11</sup> Citations are as of November 28, 2023.
- <sup>12</sup> Since JIF information is only available from 1997 onwards, and some journals were included only in later years, we impute the impact factor for earlier years based on the first year available (this applies to 11% of the articles in our samples). We include a missing dummy equal to one for these articles in our regressions where JIF is the dependent variable or included as a control variable. In addition, 2-year impact factors are not available for some journals that have only recently been included in the citation indices. This applies to less than 4% of the articles in our sample. We exclude these articles in the regression analyses with JIF as the dependent variable or as a control variable.
- <sup>13</sup> Specifically, we have assigned the following subfields of "Economics & Business" to the discipline of "Economics": "Economics," "Econometrics," "Economic Theory," "Finance," "Agricultural Economics & Policy," "Development Studies," and "Industrial Relations," as well as the subfield "Health Policy & Services" of the field "Public Health & Health Services" (since in our sample this consists mainly of articles in the *Journal of Health Economics* and *Health Economics*). The subfield "Economics" accounts for more than 84% of the articles in the discipline "Economics" in our sample. We assigned to "Sociology" (discipline), the subfield "Sociology," to "Psychology" all subfields of the field "Psychology & Cognitive Sciences" as well as the subfield "Psychiatry," to "Other Social Sciences" the field "Social Sciences" (except the subfield "Sociology") as well as all remaining subfields of the field "Economics & Business." Journals in all other fields and subfields were assigned to the residual discipline "Health and other sciences." We decided not to further subdivide the disciplines to have at least 10% of the observations in each category.



- <sup>14</sup> Merging was not successful for seven journals (39 articles) in our dataset. For these seven journals, we imputed the discipline based on the first category of Clarivate's Master Journal List (2022). In addition, Science-Metrix does not provide a journal-based classification for 15 multidisciplinary journals in our dataset (65 articles, including for example, PLOS ONE, Economics & Human Biology, PNAS, and Nature). Again, we assign these journals based on the first category of Clarivate's Master Journal List.
- <sup>15</sup> The TOP Factor Database has a community-based approach where editors and registered users can submit a journal evaluation, which Center for Open Science staff reviews before publishing the scores (for more information, see COS, 2024). For all 164 journals, the last update of the code-sharing policy was in 2021 or later. The coverage of the journals in the TOP Factor Database differs substantially across disciplines: The TOP Factor Database covers 69% of psychology journals of our sample, 38% of health and other sciences, 32% of sociology, 27% of economics, and 26% of other social science journals.
- <sup>16</sup> We focused on *code* sharing policies and considered *data* sharing policies only when code, syntax files, or computer programs were explicitly mentioned as part of "data."
- <sup>17</sup> We also double checked with the dates provided in Brodeur, Cook, and Neisser (2024) and Christensen and Miguel (2018), which focused on *data* availability policies, for 25 and 11 economics journals respectively. In general, we took the information provided by journal websites and editors for granted and did not check the extent to which these policies are actually enforced (see also the discussion in Colliard et al., 2023).
- <sup>18</sup> As a result, we are missing the adoption dates for five journals, corresponding to 68 articles in our dataset. We exclude these 68 articles from the analyses that rely on the implementation dates of code-sharing policies.
- <sup>19</sup> In economics, code is only provided in Stata (95%), Matlab (9%) and R (7%) in our sample. The percentages add up to more than 100% because some articles rely on more than one software program.
- <sup>20</sup> The shares are similar in the 2017 SOEP user survey with 76% Stata, 31% R, 19% SPSS, 10% other (Britzke & Schupp, 2019).
- <sup>21</sup> We also consider code found through references in the articles as having been disseminated through the journal because the articles are accessible through the journal website.
- <sup>22</sup> The OSF is a network for researchers to document their research projects, for example, by registering analysis plans and sharing their material. It also allows a DOI to be assigned to the code provided, making it possible to keep the code permanently available.
- <sup>23</sup> In line with these findings, OSF users and usage have increased exponentially since its inception in 2012 (see Nosek et al., 2022).
- <sup>24</sup> Miguel (2021, 196) highlights the importance of these online repositories, saying that they "have been so successful that it is easy to forget what an important innovation the professional curation, storage, and management of research data and code has been."
- <sup>25</sup> The *Journal of Political Economy* implemented a similar Level-2 policy in 2005 and the *Review of Economic Studies* in 2006. This was followed by the *Brookings Papers on Economic Activity* in 2007, the *Canadian Journal of Economics* in 2008, and the *American Economic Journals* in 2009.
- <sup>26</sup> While the upper panels of Figure 4 show that some economic journals are rather front-runners in terms of code-sharing policies, the first journal with an explicit code-sharing policy was the *Stata Journal*. The journal, due to its focus on software code, requires since the first issue in 2001 that software code is made available through the journal's website.
- <sup>27</sup> The *Biometrical Journal* was, in 2009, the first journal in our sample to implement a policy of independently reproducing the results of accepted manuscripts prior to publication (Hofner et al., 2016). However, code sharing is not mandatory: "the Editor in Chief notifies the authors ...already during the review process of the journal's RR [reproducible research] policy and strongly encourages the submission of code and data to make the article reproducible" (Hofner et al., 2016, p. 418).
- <sup>28</sup> The fifth article is published in the *Journal of Applied Econometrics*, which also strongly emphasizes the replicability of results by other researchers. While the journal has a mandatory data sharing policy (if the data are not confidential), code sharing is only encouraged but not mandatory according to the journal website (Journal of Applied Econometrics, 2024).
- <sup>29</sup> We also exclude the 68 articles published in the five journals, for which we could not obtain the implementation dates.
- <sup>30</sup> More specifically, we estimate equations of the following form:

$$y_p = \alpha + x'_p \beta + \sum_{t=1986}^{2021} \delta_t \cdot \mathbb{1}(\text{year}_p = t) + \varepsilon_p, \quad (1)$$

where  $y_p$  is a binary variable indicating whether the code is publicly available for publication  $p$ .  $x_p$  is the vector of explanatory variables (e.g., indicators for the journal's discipline);  $\delta_t$  represents the coefficients of a set of dummy variables corresponding to each publication year. Finally,  $\varepsilon_p$  is the error term. We use heteroscedasticity-robust standard errors throughout our analysis, as the variance of  $\varepsilon_p$  may not be constant across different values of the explanatory variables.

- <sup>31</sup> Studies published in early years have more time to accumulate citations. Therefore, Figure 7 controls for year of publication dummies.
- <sup>32</sup> Going in this direction, for example, Christensen et al. (2019) provide some evidence that *data* sharing increases citations when using changes in data sharing policies as instrumental variables.

<sup>33</sup> For instance, Brodeur, Cook, and Neisser (2024) find evidence that *data-sharing* policies do not reduce *p*-hacking and publication bias, cautioning against being too optimistic regarding the positive effects of mandatory research transparency initiatives.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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## APPENDIX A

TABLE A1 Most frequent journals in our sample.

Economics	
Labor Economics	79
Jahrbücher für Nationalökonomie und Statistik	62
Review of Income and Wealth	49
Economics Letters	48
Journal of Population Economics	44
Journal of Economic Behavior & Organization	43
Health Economics	30
German Economic Review	29
Applied Economics	26
Empirical Economics	25
Economic Journal	24
Journal of Health Economics	22
European Economic Review	21
Journal of Human Resources	21
Sociology	
Kölner Zeitschrift für Soziologie und Sozialpsychologie	98
European Sociological Review	94
Zeitschrift für Soziologie	67
Soziale Welt	17
Research in Social Stratification and Mobility	16
Psychology	
Social Indicators Research	76
Journal of Happiness Studies	31
Journal of Personality and Social Psychology	20
Psychology and Aging	20
Journal of Research in Personality	14
Other Social Sciences	
Journal of Marriage and Family	29
Zeitschrift für Familienforschung	26
Journal of European Social Policy	18
Small Business Economics	18
Demography	17
Health & Other Sciences	
AStA-Advances in Statistical Analysis	35
PLOS ONE	24

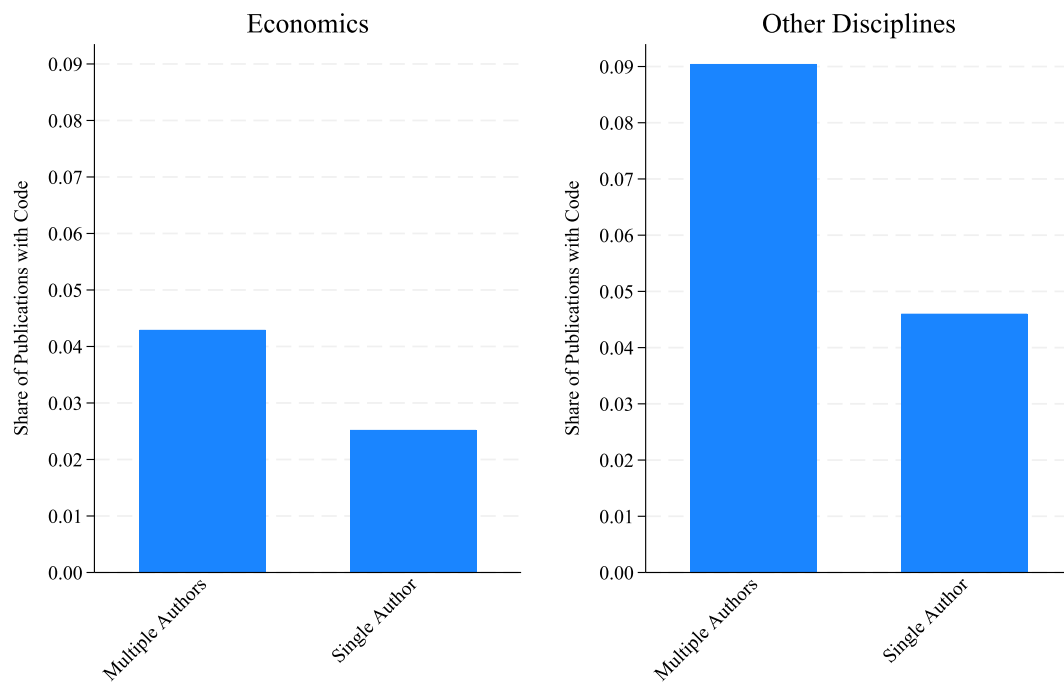


TABLE A1 (Continued)

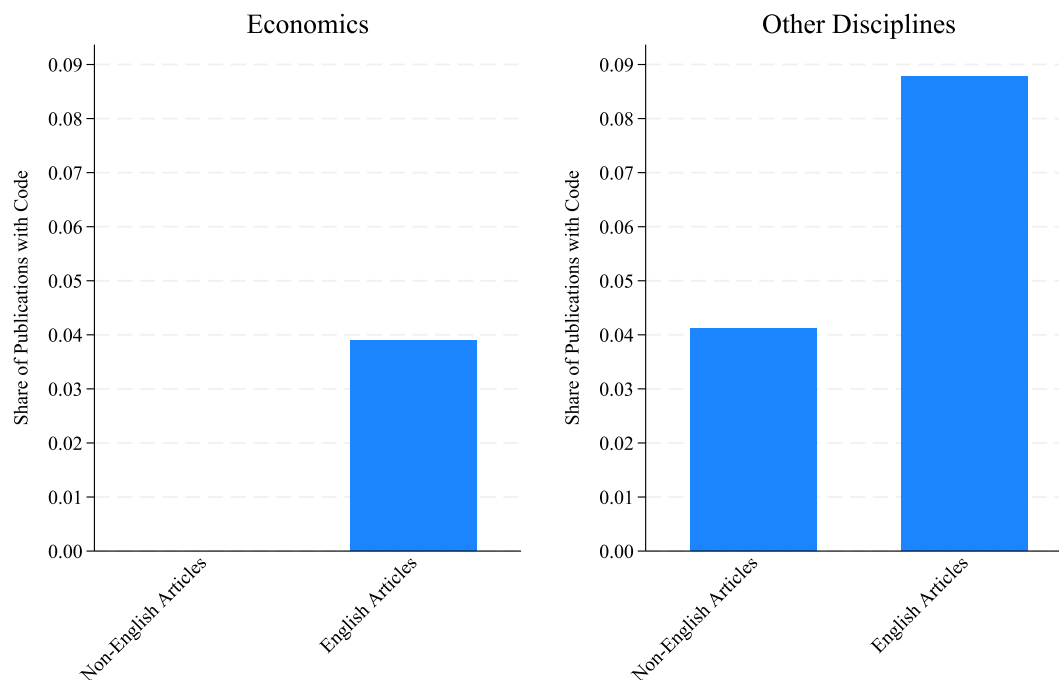
Gesundheitswesen	19
Social Science & Medicine	19
Journals of Gerontology Series B-Psychological Sciences	13

*Note:* The table lists, for each of our five disciplinary categories, the names of the journals with the most articles in our dataset and the corresponding number of articles.

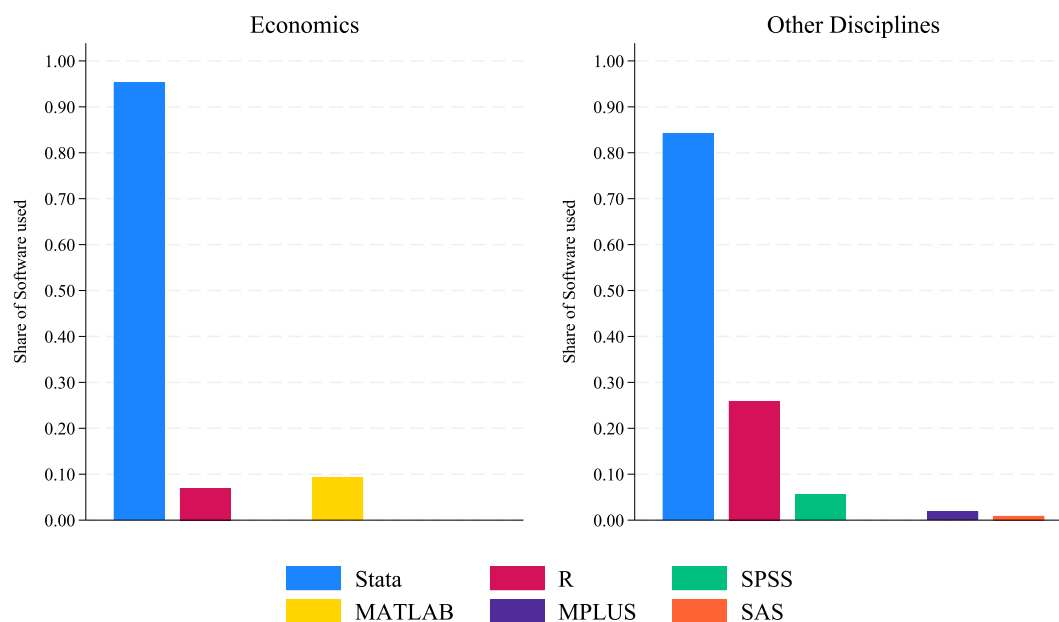
*Source:* Own counting, based on SOEPlit (2022).



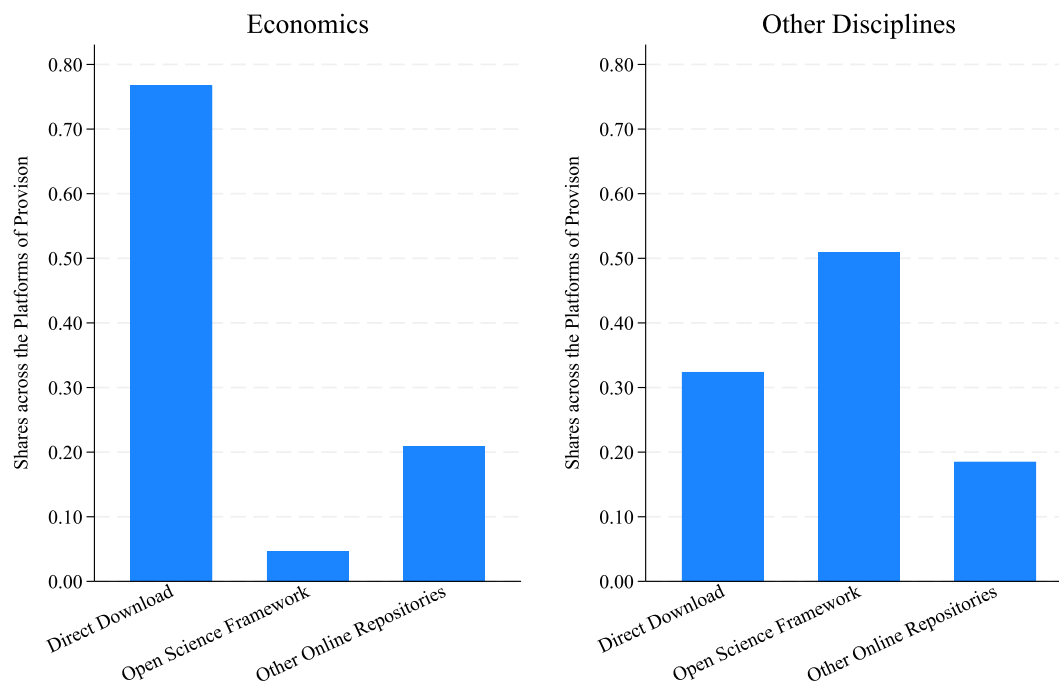
**FIGURE A1** Code availability: Single author versus multiple authors. This figure shows the share of SOEP-based publications with publicly available replication code, separately for articles written by a single author and articles with multiple authors. The left panel relates to economics, while the right panel relates to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.



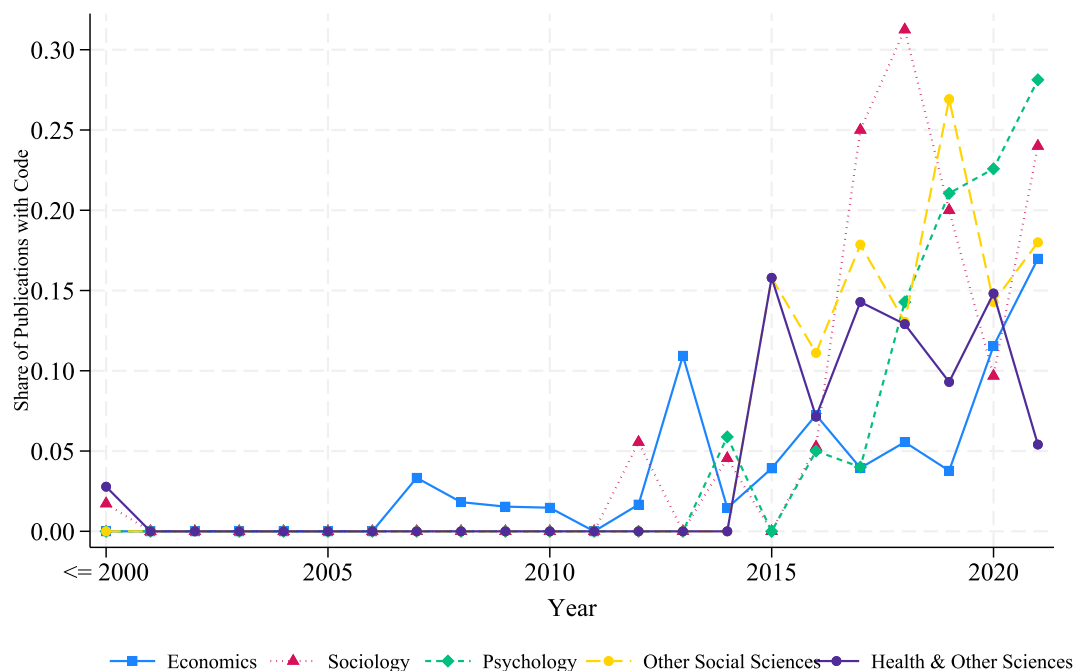
**FIGURE A2** Code availability: Language of the article. This figure shows the share of SOEP-based publications with publicly available replication code, separately for articles in English and in all other languages (mostly German). The left panel relates to economics, while the right panel relates to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.



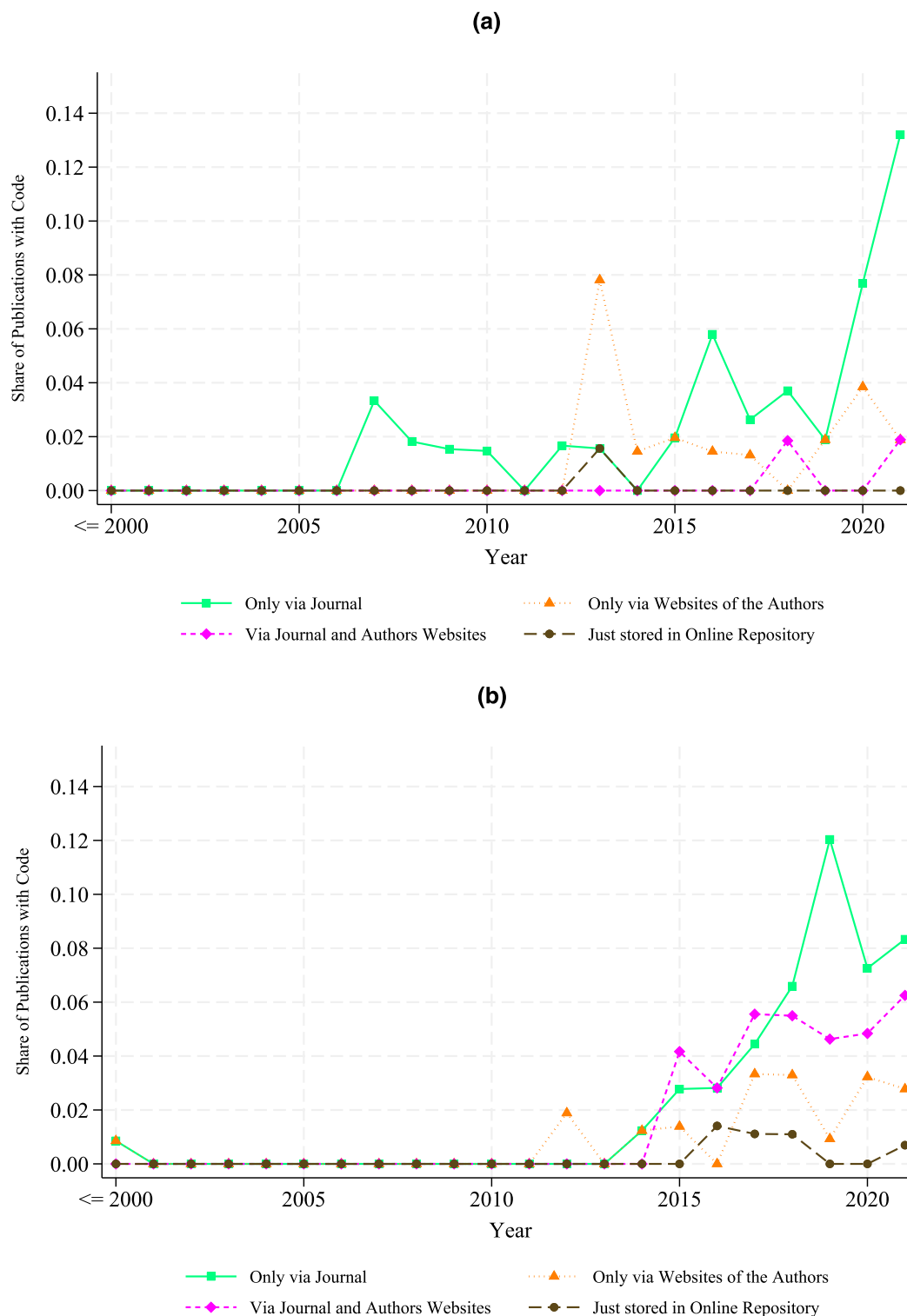
**FIGURE A3** Software used in the replication packages. This figure shows the distribution of statistical software programs used in the available code packages in our sample. The left panel relates to economics, while the right panel relates to all other disciplines. Note that the shares in each panel do not sum up to 1 as sometimes more than one statistical software is used. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.



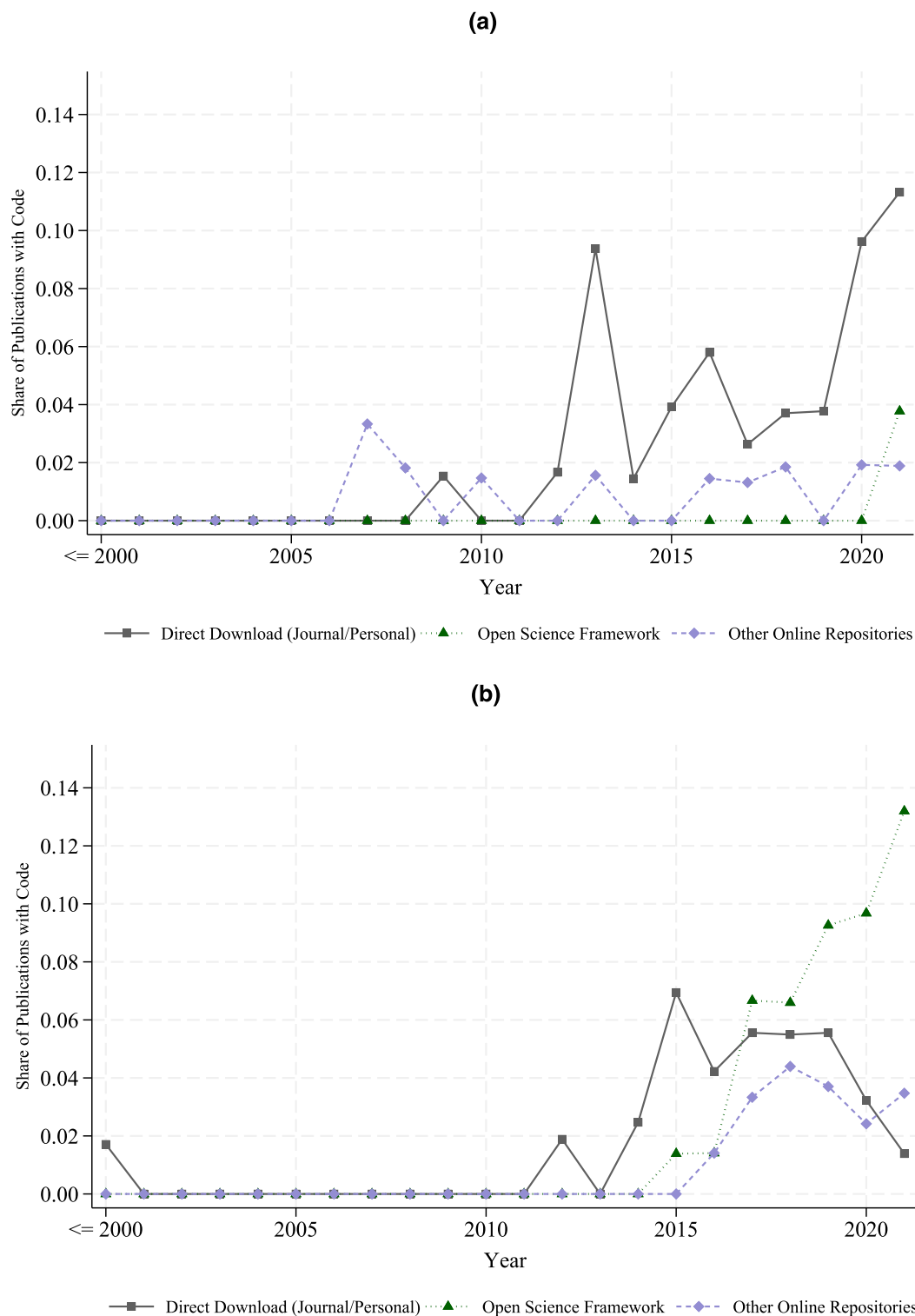
**FIGURE A4** Publications with publicly available code by storage location. This figure displays the distribution of the location in which the code is stored among all SOEP-based publications with publicly available replication code. The left panel relates to the situation in economics, while the right panel relates to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.



**FIGURE A5** Share of SOEP-based publications with publicly available code, by discipline. This figure shows the share of SOEP-based publications with publicly available replication code among all SOEP-based publications in the respective year and discipline. The left endpoints of the graph represent the average of all years before 2001, since code availability before that year is very low. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.

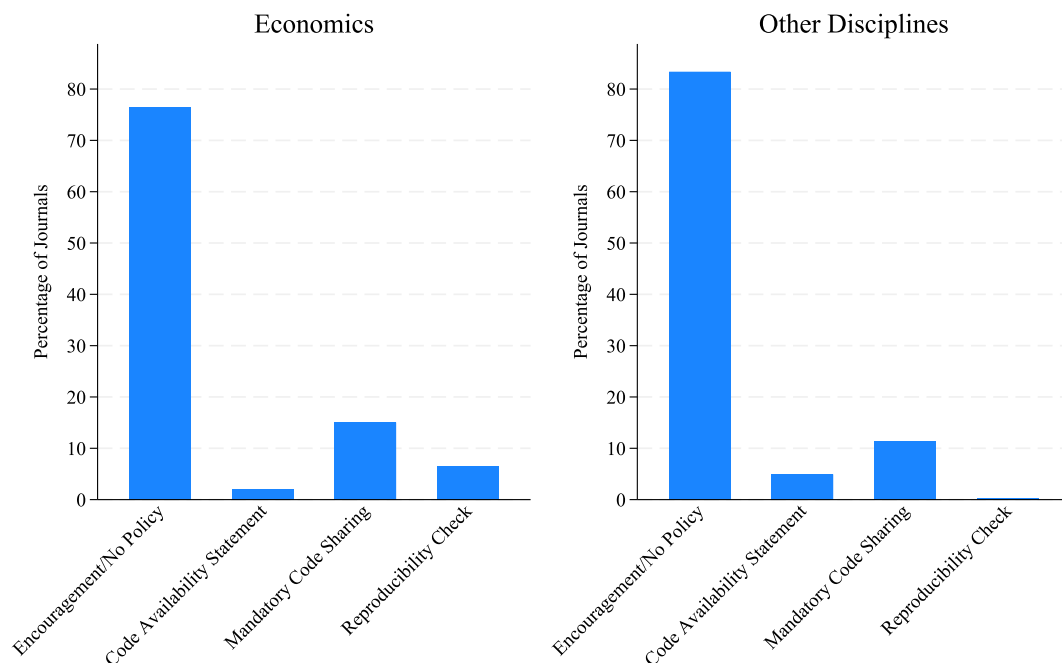


**FIGURE A6** Mode of code availability disclosure over time. (a) Economics. (b) Other disciplines. This figure shows the share of SOEP-based publications with publicly available replication code among all SOEP-based publications in the respective year and discipline, differentiating whether code availability was disclosed only through the journal, only through author websites, both through author and journal website, or only through a repository. The upper panel refers to economics, while the lower panel refers to all other disciplines in our sample. The left endpoints of the graph represent the average of all years before 2001, since code availability before that year is very low. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.

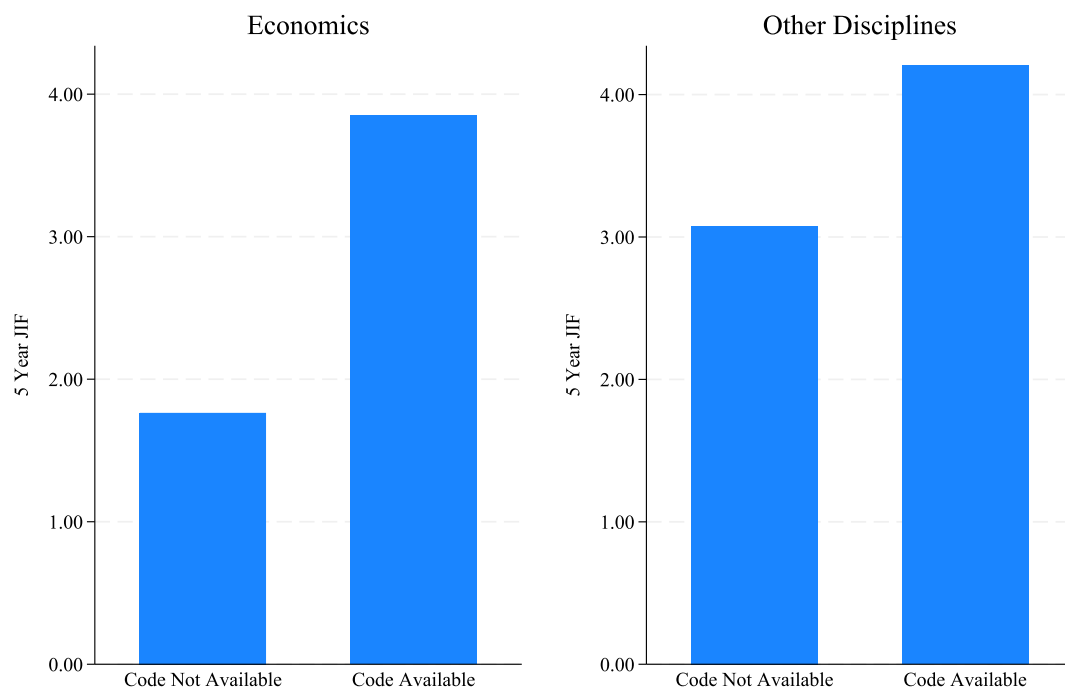


**FIGURE A7** Publications with publicly available code by storage location, over time. (a) Economics. (b) Other disciplines. This figure displays the distribution of the location in which the code is stored among all SOEP-based publications with publicly available replication code in the respective year. The upper panel relates to the situation in economics, while the lower panel relates to all other disciplines. The left endpoints of the graph represent the average of all years before 2001, since code availability before that year is very low. *Source:* Own calculations, based on SOEPlit (2022) and own research on code availability.





**FIGURE A8** Current state of code sharing policies. This figure shows the distribution of replication code policies for the 478 journals in our sample. The left panel relates to the situation in economics, while the right panel relates to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022), TOP Factor Database (2023), and own research on journals' replication code policies.



**FIGURE A9** Code availability and the 5-year journal impact factor. This figure shows the average 5-year journal impact factor separately for SOEP-publications with and without provided code. The left panel relates to economics, while the right panel relates to all other disciplines. *Source:* Own calculations, based on SOEPlit (2022), journal impact factors from Master Journal List (2022), and own research on code availability.

TABLE A2 Code availability and the 2-year journal impact factor.

	Dependent variable: Journal impact factor (JIF)				
	(1)	(2)	(3)	(4)	(5)
Code available	1.46*** (0.19)	0.64*** (0.18)			
Code × economics			0.94** (0.31)	0.96** (0.31)	0.59* (0.29)
Code × other discipline			0.51* (0.21)	0.48* (0.20)	0.36 (0.22)
Sociology			−0.01 (0.06)	0.49*** (0.08)	0.52*** (0.08)
Psychology			1.09*** (0.09)	1.13*** (0.09)	1.01*** (0.11)
Other social sciences			0.31*** (0.09)	0.42*** (0.08)	0.45*** (0.08)
Health and other sciences			1.59*** (0.24)	1.76*** (0.24)	1.66*** (0.21)
English article				1.08*** (0.10)	1.08*** (0.09)
Single author				−0.24*** (0.05)	−0.21*** (0.05)
Code availability statement					4.97* (2.32)
Mandatory code sharing					0.72*** (0.21)
Reproducibility check					2.71* (1.16)
Publication year FE	No	Yes	Yes	Yes	Yes
Adj. R <sup>2</sup>	0.03	0.17	0.24	0.27	0.31
N	2426	2426	2426	2426	2358

Note: The table presents estimates from OLS regressions with the 2-year journal impact factor as the dependent variable and robust standard errors in parentheses. Column (1) confirms the pattern from Figure 6: Code provision is associated with higher impact factors and this association remains, albeit to a lesser extent, when controlling for publication year dummies (column 2). In column (3), we additionally control for the discipline of the journal and replace the code availability indicator with separate code availability indicators for economics and for other disciplines. The picture remains similar. Controlling for year fixed effects, code availability is associated with a 0.94 point higher JIF in economics and a 0.51 point higher JIF in other disciplines. These relationships do not change much when controlling for the single-author indicator and the language of the article (column 4). The relationship also remains very similar when controlling for the journal's code-sharing policy (column 5).

\* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ . The base category for the discipline dummies is economics.

Source: Own calculations, based on SOEPlit (2022), journal impact factors from Master Journal List (2022), as well as own research on code availability and journals' replication code policies.

TABLE A3 Code availability and Google Scholar Citations.

	Dependent variable: Citation count					
	(1)	(2)	(3)	(4)	(5)	(6)
Code available	−30.3 (15.7)	96.3* (39.2)				
Code × economics			168.7* (76.7)	181.9* (77.7)	49.5 (53.2)	35.1 (47.3)
Code × other discipline			44.7* (22.0)	46.0* (20.4)	15.9 (22.4)	21.4 (22.0)
Sociology			−54.3*** (9.6)	−2.8 (11.1)	0.2 (11.2)	−14.3 (11.9)
Psychology			45.8* (22.7)	43.4* (20.4)	45.7* (20.6)	25.1 (17.2)
Other social sciences			−34.4** (10.5)	−26.0** (9.9)	−23.6* (9.9)	−28.3** (10.9)
Health and other sciences			−54.9*** (10.5)	−39.1*** (10.2)	−37.9*** (9.9)	−71.8*** (11.6)
English article				84.8*** (8.0)	86.2*** (8.1)	80.4*** (8.7)
Single author				−34.9*** (8.4)	−33.2*** (8.6)	−30.3*** (8.7)
Code availability statement					126.8 (147.8)	−86.8*** (25.3)
Mandatory code sharing					172.1 (93.4)	147.0 (85.6)
Reproducibility check					560.3 (341.4)	361.9 (194.0)
Journal impact factor						15.1*** (2.5)
Publication year FE	No	Yes	Yes	Yes	Yes	Yes
Pseudo R <sup>2</sup>	0.00	0.25	0.29	0.34	0.36	0.43
N	2518	2518	2518	2518	2450	2358

*Note:* The table presents average marginal effects from Poisson regressions with robust standard errors in parentheses and citations as the dependent variable. While the raw relationship between code availability and citations is negative (column 1), the coefficient reverses sign when publication year fixed effects are included (column 2), highlighting the importance of controlling for differences in publication years. Column (3) introduces controls for different disciplines and replaces the code availability indicator with separate code availability indicators for economics and for other disciplines. Column (4) additionally controls for the single author indicator, while Column (5) considers the journal policies on code sharing as well. Column (6) controls for the JIF.

\* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .001$ . The base category for the discipline dummies is economics.

*Source:* Own calculations, based on SOEPlit (2022), Google Scholar (2023), journal impact factors from Master Journal List (2022), as well as own research on code availability and journals' replication code policies.