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Using Containers to Validate Research on Confidential Data at Scale

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Abstract. I describe past experience with the validation server process over 10 years and several hundred users, as a means to provide proxy access to confidential data. As a modern replacement, I propose the use of containers — simulated computers that encapsulate entire software and file structures. The use of containers ensures reproducibility, reliable portability, and enables scalability. Infrastructure can be outsourced to commercial providers or users, at little to no cost to data providers. The only likely limitation to full automation is the absence of automated output vetting algorithms at statistical agencies. ~~An example is provided.~~

Keywords: synthetic data; verification server; confidential data; reproducibility, containers

Media Summary

~~The Media Summary should be written in plain language to highlight the key messages of the article, in ways that can be understood by the general public and cited by the media directly and accurately. It therefore should avoid technical terms or language designed for academic communications. It should not exceed 400 words, and more succinct.~~ Vilhuber describes how researchers have used synthetic data as a proxy access to confidential data in the ~~better~~past. Such systems have been long and expensive to develop, because trying to satisfy many different constraints on their suitability imposed by users. Instead, he suggests that modern containers — simulations of entire computer and software systems — could be leveraged as a portable, scalable, and cheaper replacement system. By packaging lower quality synthetic data in prescribed environments, and allowing users and commercial providers to support their use, then providing rapid turnaround on validation against the actual confidential data, monetary and time costs of the system for both providers and end users can be substantially reduced.

1. ~~A short history of synthetic data, verification servers, and improving access to confidential data~~

Introduction

Concerns about confidentiality in statistical products have increased in the past several years. While the new disclosure avoidance techniques introduced for the 2020 United States Decennial

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Census (Abowd et al., 2022) garnered much attention, the academic community also expressed concerns about agency plans to apply formal disclosure avoidance techniques to ~~public-use microdata files (PUMFs)~~public-use microdata files (PUMFs), and after an initial announcement, the Census Bureau delayed implementation of such methods for the ~~American Community Survey~~ American Community Survey (ACS) (Daily, 2022).

~~On the other hand, long-running~~ Part of the concern is that the application of confidentiality methods may prevent inferences that were feasibly made in the absence of those confidentiality procedures. Some of those concerns may be solved by adopting analysis methods that are congenial (Meng, 1994) to the disclosure avoidance methods, though that is not a recent problem (Abowd & Schmutte, 2015) . However, statistical agencies often attempt to provide "one size fits all" datasets for general purpose usage, as in the case of the ACS, with the goal of usability by a wide spectrum of models. One novel approach, at least at the time, was the provision of synthetic data that preserved most of the inferential validity of the underlying confidential data (Little, 1993; Raghunathan, 2021; Reiter, 2023; Rubin, 1993) . However, producing such general purpose synthetic data that are reasonably non-disclosive has proven difficult and long.

This article will set out to combine various lessons learned from both the literature and past experiments in a variety of domains to propose an alternative or complementary approach to providing access to confidential data via synthetic data. I draw on lessons learned from the analysis of several thousand replication package in economics (Vilhuber & Cavanagh, 2025), from past efforts to create custom ('bespoke') synthetic data (Nowok et al., 2017), from current technology that allows for reliably reproducible analysis (**containers**, see Boettiger, 2015, for an introduction) , and the feedback of hundreds of potential users of synthetic data in a project I co-lead until 2022 (Vilhuber & Abowd, 2022). The proposed mechanism will allow to relax some of the analytical validity of the synthetic data, but in exchange allow for rapid turnaround time for analyses, something that researchers value. A maintained assumption, informed by observing similar usages and from our own experience, is that the cost of such a system is dramatically lower, and can thus be feasibly implemented by budget-constrained federal agencies.

I will start by defining what container technology is, what particular definition of synthetic data I have in mind, and what validation and verification servers are in the social science space. I will then lay out how the fact that containers can create portable and reproducible environments can be leveraged to simplify the validation of code, allowing researchers to develop models on synthetic data, and validate on confidential data, at scale, while maintaining the confidentiality promises that custodians give to their respondents. I then discuss a concrete but to this day theoretical example, and consider advantages and (key) limitations to the mechanism. The combination of containers with a relaxation of the quality of synthetic data can allow data custodians — survey institutes or statistical agencies — to scale up access by researchers at substantially lower cost than currently implemented. In concluding, I discuss some possible extensions, including how to embed stronger privacy-protection methods such as differential privacy into both analysis and release of results.[1]

1. Concepts and Definitions

[1] At the time of this writing, at least one other project, much more ambitious and complex, has been under development for a few years, and is testing a "privacy-preserving validation server" (Burman et al., 2018; Tyagi et al., 2024). I will briefly contrast that project to the present proposal in the discussion.

1.1. **Containers.** Containers, often referred to using the name of a particular implementation by a commercial provider (Docker), are technology which enables computer processes and code libraries to be bundled and constrained. In essence, a container is a bundle of all the dependencies and code an app, or a researcher's statistical analysis, needs, into a single compact bundle or even a single file, which can then be run on any computer without (much) further ado. They can contain the data necessary for such computations, though there is also the ability to inject components — such as researcher-specific code or data — at the time a more general-purpose container is run. Containers can be hosted on a cloud platform, but can also run individually on researcher compute platforms (personal computers). They have been primarily developed to allow for lightweight but massive scaling of internet applications, which requires the same process be re-executed in a reliable fashion, i.e., in a reproducible fashion. This latter aspect is what has made it attractive for academic researchers as well, and containers have been put forward as a mechanism for reproducible research for nearly a decade at this point (Boettiger, 2015), with various commercial and academic services arising around the use of containers (Brinckman et al., 2018; Chard et al., 2020; Clyburne-Sherin et al., 2019) . Alternatives to Docker containers are Apptainer (Contributors to the Apptainer project, 2025) , various Docker-compatible Linux implementations (for instance, "Podman", n.d.), or even BSD "jails" (The FreeBSD Project, 2025).[2]

Container usage in the context of confidential data in the social sciences or in statistical agencies is sparse, to the best of my knowledge. Containers themselves are not inherently more or less secure, and need to be managed appropriately to ensure that complete privacy and security are not compromised (see Souppaya et al., 2017), though that is similar to the fundamental IT security considerations all hosts of confidential data must implement.[3] In this article, I do not address container security per se, and in fact, as I will outline in an example later, container usage in the confidential environment is not necessary, albeit possibly convenient.

1.2. **Synthetic Data.** The idea for what is now called "synthetic data" was laid out more than three decades ago by Rubin (1993): Using models trained on the confidential data, (multiply) impute some or all the values for a simulated population, and release to the public. The resulting file does not comprise any single person's "real" data, but is expected to be statistically similar to the unreleased confidential data. Since the original proposal, synthetic data in the context of statistical agencies and survey organizations has been much discussed. The primary concerns are two: how protective are synthetic data, and how fit for purpose are they? When statistical agencies aim to use synthetic data as a replacement or enhancement for other methods of disclosure avoidance, both issues are important. However, this article will not contribute to clarifying that, and the interested reader is pointed at Drechsler (2021), Drechsler and Haensch (2024), Raghunathan (2021), and Reiter (2023) and in particular, Raghunathan and Chaney (2023) and Raghunathan and Hotz (2024). I note that synthetic data is also often discussed in the context of machine learning and the training of AI models, often with a different focus than that of statistical analysis. Rather, in that context,

[2] Containers are often, but not exclusively, associated with Linux. There are container implementations for computers running Windows and macOS, typically running within a virtual machine (a simulated computer) running Linux. It is technically feasible to run a Windows container. Virtual machines are a more complex method of simulating an entire computer, but introduces more complexity in terms of the transparency, a key feature in this article.

[3] Considerations include compliance with General Data Protection Regulation (GDPR) or Health Insurance Portability and Accountability Act (HIPAA).

synthetic data is used to help develop algorithms, sometimes by explicitly not making the synthetic data representative, for instance to work around inherent biases. While not the primary focus, I will refer back to those domains in one particular aspect that makes synthetic data there useful, namely for the testing of code.

1.3. **Verification servers, and improving access to confidential data.** Because of the novelty (in this context) of synthetic data, creators of such data first needed to convince privacy custodians that synthetic data was protective of the underlying respondents. They then need to convince users of the data that the data have analytic validity, and can serve as valid and possibly universal replacements to more traditional public-use data (Reiter et al., 2009).[4] In this context, the term **verification server** appears to be used when the answer provided to users is a quality measure of some kind, and the term **validation server** when answers derived from the actual confidential data (and possibly modified for confidentiality purposes) are provided to the user (and the public). The latter is more akin to a **remote submission server**, except that the data used to prepare submissions is meant to actually replace the need for submissions, at least in the long-run.

Long-running pilot projects with (non-formal) synthetic microdata products (SynLBD (Kinney et al., 2011; U.S. Census Bureau, 2011; Vilhuber, 2013), SIPP Synthetic Beta (Benedetto et al., 2013; Reeder et al., 2018; U.S. Census Bureau, 2015a)) came to an end in 2022 (Vilhuber & Abowd, 2022). [5] These pilot projects made use of a publicly accessible analysis server (~~the "Synthetic Data Server," SDS~~Synthetic Data Server (SDS)) housing synthetic data, authorized for release in this environment by the Census Bureau and the IRS (e.g. U.S. Census Bureau, 2015b), combined with a mechanism to re-run the analysis using confidential data, housed in the confidential computing environments of the U.S. Census Bureau.[5] Researchers obtained (fast) access to the ~~SDS~~SDS, where they interactively developed their code, using the releasable synthetic data, in ~~an~~ a desktop-centric environment specifically designed to mimic the Census Bureau's environment.[6] Researchers were free to develop any code in any kind of structure, but were not allowed to remove the data from the SDS. Analysis code that was to be validated was restricted to the software available at the Census Bureau. Requests to validate the results obtained from prepared code were ~~sent~~ submitted via email to designated Census Bureau staff, who then manually ran the code ~~(~~on Census Bureau servers, often times debugging it~~)~~, and handled disclosure avoidance analysis at the Census Bureau on behalf of the researchers. The modeling and analysis code provided by the researchers served to improve subsequent versions of the synthetic data. Figure 1 illustrates the process flow.

[4] This problem, of course, is not unique to synthetic data and applies to any modification applied to released data.

[5] ~~The SDS server was funded in part by NSF grants SES-1042181 and SES-1131848 as well as Alfred P. Sloan Foundation Grant G-2015-13903. The last of the funding through these grants ended in 2018, and availability after that time was funded through John Abowd's Edmund Ezra Day chair at Cornell University, on a shoestring budget.~~

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[6] Technically, the Cornell-based server ran an NX remote Linux desktop. Shell access or remote submission were not allowed.

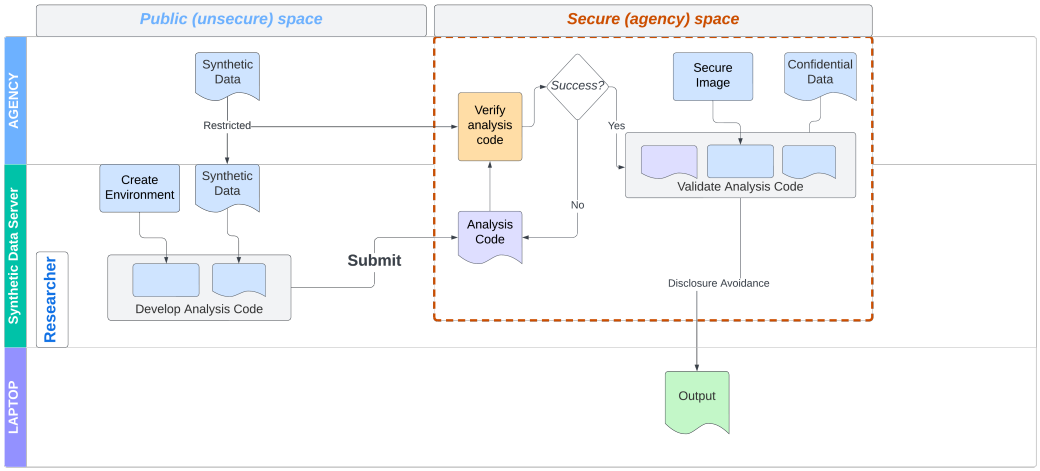

Figure 1. ~~Processing principles~~ Process flow of validation using the Synthetic Data Server

These pilot projects had two key goals, and a secondary benefit. The first goal was to develop new, analytically valid public-use data products based on confidential data that could be released to the public, much like the current public-use data products (such as the Current Population Survey, CPS, and the aforementioned ACS), replacing the need for researchers to access confidential data directly. The second goal, in support of the first one, was to allow researchers to contribute to the development of such products, and iteratively improve the data products. The secondary benefit accrued to the participating researchers: As a quid-pro-quo for contributing to the improvement of the data product, they obtained faster but indirect access to the results of analyses run on the confidential data.

2. Lessons learned from the SDS mechanism

Several lessons emerged from the ~~SDS~~ SDS mechanism. While many researchers used the data to write papers,[7] and even organized conference sessions specifically around the use of the data,[8] [8] even more researchers only "tried out" the data. While over 100 researchers were granted access to the server to access the ~~SSB~~ SIPP Synthetic Beta (SSB) in the first five years of its availability (Figure 2), far fewer published using the ~~SSB~~ SSB data. Almost none of the published articles

[7]All publications directly funded by the supporting NSF grant, or using the NSF-funded server, are listed at https://www.zotero.org/groups/5595570/sds-nsf-1042181/library. Some publications were prepared by NSF-funded project personnel and should not be directly included in a publication count of "users." Most publications were included in this list after a bibliographic full-text search for the grant identifiers. Some researchers may not have reported the published article to the project team, or mentioned the support of the grant to the server they used in their acknowledgements.

[8]~~LERA session "Data Gold! Exploiting the Rich Research Potential of Lifetime Administrative Earnings Data Linked to the Census Bureau's Household SIPP Survey", at the Allied Social Sciences 2016 Annual Meeting (American Economic Association, 2016).~~

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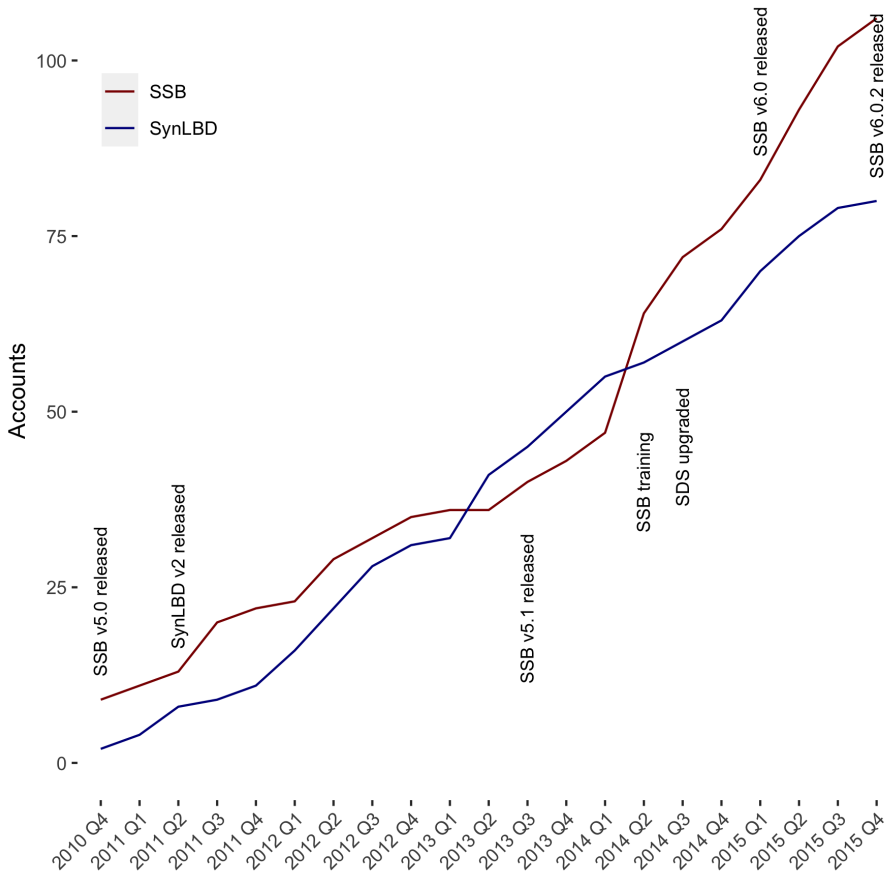

Figure 2. Computer accounts on the SDS over time

actually used the results produced using the synthetic data. Comparison of parameters obtained from synthetic data and from confidential data using confidence interval overlap, a measure of congruence between the synthetic data and the confidential data introduced by Karr et al. (2006), was very heterogeneous even for a given dataset across and within projects (Table 1).[9] While the results in Table 1 do not take into account a distinction between key and nuisance parameters (simply comparing all parameters estimated in researcher-provided models), authors may have simply been very hesitant to use the parameters estimated on the synthetic data.

Thus, a core goal of the synthetic data — to replace the confidential data in researchers' analyses — was not being met, even when the synthetic data actually ~~was~~ w a very good stand-in (note the SynLBD project B with a mean confidence interval overlap of 87%). Nevertheless, the synthetic

[9] Due to technical issues, the selection of projects is a convenience sample. The analysis was run ex-post, without the collaboration of the original authors, by injecting code into the original authors' analysis code. This often failed, especially for more complex code. The results using the confidential data were obtained by Census Bureau staff, and released to the author of this article after disclosure avoidance, several years ago.

User	Request	Mean	75th	90th	Max	Dataset
A	1	0.16	0.25	0.72	0.89	SynLBD
A	2	0.10	0.00	0.52	0.92	SynLBD
B	1	0.87	1.00	1.00	1.00	SynLBD
C	1	0.22	0.51	0.72	0.99	SynLBD
D	1	0.49	0.79	0.87	0.98	SSB
E	1	0.39	0.56	0.63	0.94	SSB

Table 1. Distribution of Parameter-specific Confidence Interval Overlap, for selected projects

The table presents the distribution of overlap in parameter-specific confidence intervals (Karr et al., 2006) across a small number of projects (for selection, see text). The overlap is quantified as the percentage of the length of the smaller interval that is contained within the larger interval, where the pairs of intervals are defined by running the same code on synthetic and confidential data. Each row shows mean and selected percentiles from the distribution of such comparisons across all the parameters of the specific model.

data were complex enough to allow for development of models without access to the confidential data, what I would call "good enough data."

Anecdotal evidence from both my own and Census staff's attempts to use author-provided computer code to run the analysis on the confidential data demonstrated challenges in reproducibility. Authors might hard-code intermediate findings, rather than letting the data drive the analysis, and would otherwise not fully leverage the similarity between the two computing environments. These lead to time-intensive human debugging, or multiple rounds with authors, neither of which are an efficient and satisfying process.

More interestingly, multiple authors treated the synthetic data access as a gateway process for access to the confidential data. Knowing that the synthetic data did not contain all the features they needed for their analysis, but having to wait for permission to access the more detailed confidential data in the ~~Federal Statistical Research Data Centers~~Federal Statistical Research Data Centers (FSRDCs), authors used the synthetic data to prepare analyses and explore the data. Figure 3 shows an early analysis of the first 106 users of the ~~SDS~~SDS, and subsequent usage of the ~~FSRDC~~FSRDC.

Importantly, in the initial phase of the projects, turnaround (submission of validation request and receipt of validated and privacy-protected results) was quite fast - single-digit weeks, rather than the multi-month process of obtaining access to the ~~FSRDC~~FSRDC. However, the introduction of new disclosure avoidance procedures at the Census Bureau, and the lack of integration of those procedures into the validation process, greatly increased the time lag in the second half of the projects.

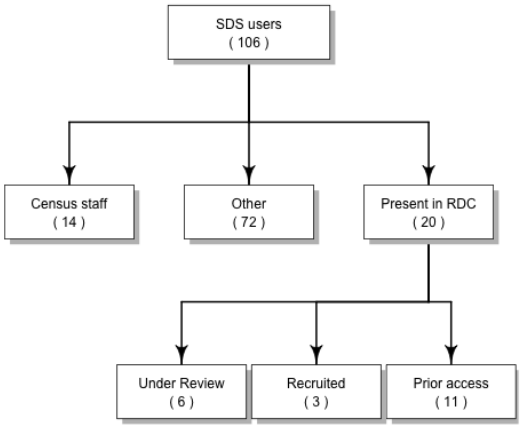

Figure 3. SDS users and access to FSRDC

3. Scaling up access to confidential data

If data cannot be made available due to intractable disclosure avoidance issues, yet access should be broadened, what can agencies do? The pilot projects described earlier were not set up to scale, and yet I argue that they demonstrated a need for such a process. The number of researchers gaining access grew continuously (see Figure 2). Special sessions at conferences were organized around the data accessed in this fashion. In general, based on ~~conversation of the author~~ my conversations with various researchers at conferences and by email, researchers were happy with the ability to access such data without having to request a full-blown project in an ~~FSRDC~~FSRDC, but were somewhat frustrated by the process.

Statistical agencies and research institutes have explored various ways to scale up access to confidential data. To cite a few examples, Statistics Canada ~~had~~ has the Real-time Remote Access (RTRA) process, Norway has the Microdata.no system, the Bank of Portugal uses a two-stage system combining a remote desktop and validation (Guimarães, 2023), and Barrientos et al. (2018) proposed a differentially private verification server.

Many such processes have limitations that limit their utility for researchers. The aforementioned Statistics Canada and microdata.no systems strongly limit the type of ~~analysis that is~~ analyses that are feasible by restricting the software keywords that can be used (RTRA), by creating a structured new statistical language (microdata.no), or by limiting the types of analysis that can be run and validated (Barrientos et al., 2018). Users of the Bank of Portugal's system still need to use the remote desktop system, similar to the SDS outlined before, because the data hosted there is not authorized as a full public-use product.

The issue is compounded by well-documented problems with the reproducibility of code in the social sciences. Heuristically, many of the problems with the SDS arose because the code failed to reproduce during validation, even though it was run in a very similar environment to the development environment. Researchers in the social sciences appear to rely heavily on interactive computing,

with code produced subsequently failing simple reproducibility tests.[10] Examples abound, and can often be gleaned from the fact that many of the reproducibility meta-studies only succeed in reproducing a small number of studies due to limitations in personnel time.[11] In a sample of over 8,000 replication packages associated with high-profile economics articles, only 30% had some sort of master script.[12] This is also my impression from our own efforts at the LDI Replication Lab supporting the AEA Data and Code Availability Policy, though we no longer make a systematic effort to categorize this. In part to cater to this need, remote-access or local secure access in the form of physical or virtual secure data enclaves are still the dominant - but expensive - way to access confidential data. The dominant method of access thus forces researchers to choose between lower quality data in an environment that corresponds to their preferred computing method, and higher quality confidential data in environments that are expensive for researchers, data providers, or both.

4. Desiderata

Drawing on the experience from the SDS pilot projects and other remote access methods used in the past, as well as looking at newer technologies that have emerged in the last decade, I suggest that a new, scalable mechanism to provide access to confidential data should have the following desirable characteristics:

- [D1] the mechanism must support arbitrary modeling approaches and ideally a large number of programming languages
- [D2] the mechanism must allow for development of models by researchers that are close to their "normal" method of developing models
- [D3] the mechanism must be low-cost for the data provider, scaling at best sub-linearly with the number of users of those datasets
- [D4] the mechanism must be low-cost for the data user, imposing at best marginal costs on their existing research infrastructure (software, computers)
- [D5] the privacy-protected data provided as part of such mechanisms must be good enough to allow for complex modeling
- [D6] validation, if necessary, must be fast - on the order of hours

[10] I define "interactive computing" as any sequence of computational codes that must be explicitly — through edits — adapted to the environment it is running in, and/or does not have a streamlined workflow that can be triggered from a single file, regardless of workflow technology. Examples of workflow management "systems" range from `make` (1976) (Association for Computing Machinery, 2003) to `Snakemake` (Mölder et al., 2021), to literate programming tools such as `Sweave` (Leisch, 2002) and Quarto (Allaire et al., 2024), to simple concatenated calls to software (canonical `run.sh`).

[11] Stockemer et al. (2018) note "lack of organization in code and data presentation was the main reason that we were unable to replicate some results" in political science articles. Stodden et al. (2018) notes that only 32% of packages in Science required only minor or no effort to reproduce, though some of the reasons listed are unavoidable (GPU setup, custom hardware) and not related to workflow issues. For the economics journal studied in Herbert et al. (2024), only 24% required no change to the code in order to be able to run, even when the ultimate results was fully reproduced.

[12] Code run in November 2023, searching for any filename that contained the strings 'main' or 'master', the most common name used for control code in economics. I am not aware of a similarly comprehensive collection for other social sciences.

Note that public-use data, as historically provided by statistical agencies, satisfies all of these criteria, except for the last one. Should statistical agencies actually offer validation even for such public use data, as Reiter et al. (2009) have argued? Traditionally, they do not, and leave it up to individual researchers to "self-validate" by requesting access to confidential data in a time-consuming fashion.[13]

5. A Proposal using Containers

I ~~demonstrate~~ describe a simple scenario that satisfies most of the desiderata, using containers. Containers ~~, often referred to using the name of a particular implementation by a commercial provider (Docker), are technology most often, but not exclusively associated with Linux, which enables computer processes and code libraries to be bundled and constrained. In essence, a container is a bundle of all the dependencies and code an app, or a researcher's statistical analysis, needs, into a single compact file, which can then be run on any computer without (much) further ado. Containers can be hosted on a cloud platform, but can also run individually on researcher compute platforms (laptops). The purpose of using containers is to provide users with access to synthetic data and coding resources such that their analysis is easily portable, and verifiably reproducible. Containers can easily~~ can easily be validated for reproducibility before they, or the code they used, are then forwarded to the confidential computing environment. ~~Once determined to be reproducible, they can then extend the analysis to use confidential data, and enable a wide spectrum of plug-in disclosure avoidance measures as well.~~ Crucially, all validation of reproducibility can be performed prior to validation using the confidential data, on open, possibly commercial platforms. Only once reproducibility is confirmed is the same analysis model ported to the confidential data. Once determined to be reproducible, the analysis is extended to use confidential data, and could use a wide spectrum of plug-in disclosure avoidance measures as well. The concept here is similar in principle to a "Common Task Framework" (Liberman, 2010, 2014; Liu & Salganik, 2019), but applied to the access problem around confidential data, not to a validation or holdout dataset (Donoho, 2024; Liu & Salganik, 2019).[14]

The use of cloud providers removes the requirement for users of the synthetic data to install anything locally. The open-source nature of the container technology, on the other hand, allows users to do so, when they want to, or when they have to. The use of containers enforces reproducibility out-of-box when using synthetic data~~, as well as streamlines~~ . Furthermore, containers enable scalability.

Finally, the combination of assured reproducibility and easily scalable computation allow for streamlined validation against the confidential data~~(~~, which is in essence a replication of the analysis on the synthetic data~~). Furthermore, containers enable scalability.~~

~~Codeocean is a commercial service facilitating that process by making the resources available through a web browser, though the basic functionality can be achieved on any container system. Other services in this space include Options include Wholetale, Onyxia, and many others.~~[15] ~~Finally,~~

[13] See ~~Armour et al., 2016~~ Armour et al. (2016) for one example of such a project, affecting the widely-used Current Population Survey.

[14] I thank an anonymous referee for having pointed out this analogy.

[15] ~~An earlier version of this presentation mentioned Gigantum. As is not unusual in this space, Gigantum no longer functions as a company. However, with the right setup, the open-source specification of most current container technology do not depend on any single provider.~~

~~users who wish to not use such services can also typically provide their own setup for the synthetic data component, at very little additional cost or effort. Many university computing system provide some support on their high-performance computing clusters. For data providers, the tools used (containers) are widely used by numerous cloud providers, are transparent in how they are built, and allow for in-depth security scanning while retaining much of the flexibility that researchers and IT providers seek~~. The streamlining, in turn, allows for low-cost rapid turnaround, quickly providing feedback and possibly results to researchers who otherwise do not have access to the confidential data. And by doing so quickly, the need to have complex and fully analytically valid synthetic data in the first place may no longer be binding. This, in turn, allows data providers to reduce the amount of time and effort devoted to developing complex synthetic data, instead focusing on creating plausibly complex, possibly custom-generated, low fidelity synthetic data, at low or no cost to disclosure avoidance budgets.

The use of containers in this way is novel as a systematic way to provide scalable, potentially high-throughput validation, and differs in usage from previous methods, such as the Cornell Synthetic Data Server. Containers have been used in a small number of well-published instances in the economics literature for precisely this kind of purpose, and are well-understood in the computer science and statistics community (Boettiger, 2015; Moreau et al., 2023). Nevertheless, acceptance in the ~~economics~~ social science community is not great, so far. In the same 8,000 replication packages in economics mentioned earlier, only 0.13% had used containers. While hard evidence in other social sciences is difficult to come by, none of the studies that analyzed reproducibility in the various social science disciplines mention the use of containers as the primary tool to ensure reproducibility in any of the packages they have analyzed.

5.1. **Details.** Reproducibility is important for synthetic data products when there is a validation or verification process involved. In such a setting, data users will first use the synthetic data to build and test their code for a desired analysis. Once the user is satisfied with the code used to perform their analysis, they can request validation or verification, and their code will be run by the data provider on the confidential data. Output from the analysis on the confidential data will then have to satisfy the data provider's disclosure avoidance procedures before it can be released to the user. In the case of validation, the results from the second run on confidential data are released to the user, possibly confidentialized (U.S. Census Bureau, 2024). In the case of a verification server, the user only receives a (non-disclosive) message indicating whether her results from the first run can be considered to be inferentially valid or not (Barrientos et al., 2018).

One problem that can arise when maintaining a validation process is that the computing environment on the data user's end does not exactly match the computing environment for the internal validation. This can lead to validation attempts that fail to run correctly or at all, which increases the wait time for data users and the staff time involved in performing the validation at the data provider. In order for this process to run smoothly, the data user's code needs to be reproducible. This ensures that the user's code can be easily transferred and run on the confidential data. This can be achieved by using a ~~"container."~~ "container." A container collects all of the necessary libraries, dependencies, and code needed to run an analysis in a single package. This container can then be downloaded to any machine and used with the local system to run the application. Crucially, container systems usually have the capability to either rebuild containers in a trusted environment, or to provide to users pre-configured secure containers that are also authorized to run in the secure area hosting the confidential data. In most cases, the core container itself does

not need to be transferred, only a comprehensive, easily parsable recipe to build such a container ~~.~~ from known sources, and the user's model-specific code. Both the recipe (called a 'Dockerfile') and the user-provided model code, are plain-text, and adhere to known language specifications, which allows for easier security vetting of the code.

6. A detailed use case when using synthetic data

In this section, we walk through the process for a specific use case. The Census Bureau, data owner (custodian) of the confidential SIPP file merged with administrative data known as the SIPP Gold Standard file, makes a synthetic version of the Gold Standard file available as the ~~"SIPP Synthetic Beta file" (SSB)~~ SSB (Benedetto et al., 2013). The container host in the public domain in this case is Codeocean, which provides cloud-based access to Docker-based containers (called ~~"compute capsules").Users log in via a simple web browser, with no install required~~"compute capsules").[15] We use the example of Codeocean here, because they provide a relatively user-friendly interface for development of code, while retaining the requirement to have a hands-off, non-interactive run as a pre-requisite for publication. Crucially, Codeocean provides access to Stata and ~~Matlab~~ MATLAB compute capsules, covering 95% of economists' software needs. Users log in via a simple web browser, with no install required. A Codeocean capsule can, however, also be used by researchers on their own workstation, as long as they have Docker installed (or a compatible container runtime) and have a Stata or MATLAB license. Because of the standards-based approach, it is also straightforward to exchange the configured Codeocean-generated ~~"base image"~~ "base image" for a security-vetted base image within the confidential environment~~.~~, something we return to later.[16] Finally, users who wish to not use such services can also typically provide their own setup for the synthetic data component, at very little additional cost or effort. Many university computing system provide some support on their high-performance computing clusters. For data providers, the tools used (containers) are widely used by numerous cloud providers, are transparent in how they are built, and allow for in-depth security scanning while retaining much of the flexibility that researchers and IT providers seek.

In this configuration, the Census Bureau ~~can use~~ could allow Codeocean to house both the synthetic dataset as well as setup and configuration code that will assist the data user in creating code that is reproducible. The data user can then build on the setup and configuration code provided by the Census Bureau to perform their desired analysis. To perform the analysis on the synthetic data, users may either run the code directly on Codeocean by paying for access to computing resources~~(Codeocean also provides a limited amount of storage space and computing time for free),~~ [17] or they may download the compute capsule, including the synthetic data, to their local machine and use their own computing resources. When the user requests validation, ~~the~~ they provide or point to the compute capsule (containing code and any external data). The Census Bureau can

[15] There are many commercial providers able to run Docker containers.

[16] The basic functionality can be achieved on any container system. Other services in this space include or have included Wholetale (Brinckman et al., 2018; Chard et al., 2020), Onyxia, and many others. An earlier version of this article mentioned Gigantum, and linked to the website of Wholetale. As is not unusual in this space, Gigantum no longer functions as a company, and Wholetale, as an academic, externally funded pilot project, is no longer available. However, with the right setup, the open-source specification of most current container technology do not depend on any single provider.

[17] At the time of writing, Codeocean provides a limited amount of storage space and computing time for free to academic users.

~~download the user's compute capsule,~~ then securely rebuild the container (if necessary), and make minimal ~~changes to exceeute~~ (automated) changes to execute the analysis in a secure computing environment with the confidential data. By ensuring that everything can run within the Codeocean compute capsule using the synthetic data, it also ~~ensures~~ makes it very likely that everything can be run within the associated compute capsule's container using the confidential data, even when the confidential data is not housed on Codeocean or any publicly accessible service. In addition to providing a location for the Census Bureau and data users to share access to the synthetic dataset and code, ~~it also ensures~~ this mechanism also greatly increases the probability that the analysis will run correctly for both the data user and on the confidential data.

6.1. Development of code on open compute servers using synthetic data. ~~This repository itself is the code. The code is written in Stata, and is confirmed to run on in this compute capsule.~~

~~Basic structure~~ Basic structure of Codeocean's existing validation process[18] imposes a strict separation between code, immutable data, and reproducible results:[19]

- all code is under ~~'/code'~~ `/code`
- all data are under ~~'/data'~~ `/data`
- all outputs MUST be written to ~~'/results'(https://help.Codeocean.com/getting-started/uploading-code-and-data~~ otherwise they are lost.

Outputs are regenerated at each run, and the history of such runs can be found (for the developing user) in the right pane. When the user, at the end of the development process, requests publication of the compute capsule, only the last run is published, together with code and data.

To facilitate this file organization for the user, ~~the template codeincludes a `config.do`~~ template code, provided by the agency, can include a configuration file, which applies best programming practices by defining ~~some~~ global variables for file paths that are used elsewhere in the code~~. It~~, and which can be modified by runtime environment variables. For instance, the default file path to the data location may be supplied by the operating system in the confidential environment, switching where any user code will look for data. On the open compute server, the same configuration file would seamlessly point to the synthetic data. The template code also instantiates logfiles, which are also written to ~~'/results'~~`/results`, which allow for verification of what happens during runtime.

Stata, R, and many other programming languages use external packages of code (libraries) to augment native capabilities. Initially, these need to be installed over the internet. However, there are various ways to address the issue at subsequent installations:

~~1.~~ (1) Packages can always be re-installed from source ~~2. Packages~~ at runtime; (2) packages can be installed by a programming-language specific install script at (first) runtime, and stored locally~~. 3. Packages~~ ; and (3) packages can be incorporated into the container image itself (package installation is included in the recipe.

Codeocean has the ability to do the third method, via a ~~"~~"post-install~~" script and environment setup (see here(https://help.Codeocean.com/getting-started/the-computational-environment/using-the-postinstall-script here(https://help. Codeocean. com/tips-and-tricks/language-specific-issues/using-stata-on-code-ocean)).~~

[18] See https://help.Codeocean.com/getting-started/uploading-code-and-data/paths

[19] While there are various standards on the publication of research code, this is not meant to be yet another one. This is purely a requirement of the validation process, as implemented by this provider. The data custodian would need to define what their required structure is, which may or may not adhere to a specific code publication standard.

~~It can also support the first method during runtime (while connected to the internet). Because each run of Stata is transitory, there is no easy way to accomodate the second method.~~" script that is run when the environment is setup (the project-specific container image is built). This embeds any such libraries into the container image, rendering subsequent internet access unnecessary for the software to run. However, this particular environment also supports the two other methods. This could lead to failure in a confidential computing environment that does not allow for internet access, and will need to be specified to users.[20]

I note that while hosted on Codeocean, the same image, once built, is re-used, and packages installed using the third method are not re-installed. However, when exporting a capsule, only the build script is exported, and a replicator would need to rebuild the container, thereby also re-installing any packages. This can lead to version discrepancies when packages cannot be pinned to a particular version (as is the case with Stata).

6.2. **Validating reproducibility.** ~~In its base configuration, Codeocean~~ The Codeocean interface signals to researchers the successful completion of ~~a run of~~ the controller script ~~'run'~~ (called `run`) in the right pane of the user interface~~, indicating to~~. To the custodian of the confidential data, this indicates that the code is verified to execute without error on the synthetic data. The results produced by this specific run of the controller script, and not any previous interactive run, are the results provided in the "results" pane. It is important to highlight here that the Codeocean implementation preserves no outputs from prior runs in the "results" pane and folder, only from the latest run. It is thus not possible for researchers to create output in a prior run, then to comment out code that would then not be reproduced in a subsequent run in the confidential environment. Only fully automated complete runs produce all the expected output. This is important for scalability and efficiency, as it reduces the need for extensive debugging, on the researcher side, and allows for rapid assessment of basic reproducibility by the data custodian.

6.3. ~~**Concrete example: Estimating economic returns to education in the SIPP.** This exampleruns a Mincer equation~~

6.3. **Estimating Economic Returns to Education in the SIPP.** I now provide a concrete, albeit only theoretically possible, example. In this example, code to estimate a standard Mincer earnings equation (Heckman et al., 2003; Mincer, 1984) on the SIPP Synthetic Beta data ~~(need cite)~~(U.S. Census Bureau, 2024). The code ~~is~~ as provided here is in Stata, the dominant statistical programming language for economists (Vilhuber et al., 2020), though it could just as easily have been produced in any other statistical programming language.[21] The code is split into 4 pieces, tied together by a ~~script~~(system-defined) controller script. Listing 1 provides the code for the main analysis in this example. The fully worked out example can be found at Github. ~~The environment is specified through a Dockerfile.~~

Listing 1. Example Analysis Code in Stata

```
include "config.do"
```

[20] The use of software-specific environments in R, Python, Julia, and also Stata might also render subsequent internet access unnecessary when using the second method, but also requires software-specific checks to verify whether this is actually done correctly.

[21] Note that the current SSB access mechanism (U.S. Census Bureau, 2024) requires the use of Stata or SAS.

```
use ${inputdata}/${SSBprefix}1.dta, clear
/* data preparation omitted */
**Specify dependent variable, endogeneous education variable, and rest of the speci
local depvar log_total_der_cpi
local educvar educyears1
local spec1 "age age_sq i.birthyear i.race foreign_born hispanic i.state married"
local spec2 "potexp potexp_sq i.birthyear i.race foreign_born hispanic i.state marr
local specs ""`spec1'" "`spec2'""
%DIF >
**Loop through regressions, by gender
eststo clear
fvset base 1958 birthyear
foreach g in 1 0 {
foreach spec of local specs {
    eststo: reg `depvar' `educvar' `spec' if male==`g'
    ↪ eststo: ivregress 2sls `depvar' `spec' (`educvar' = i.birthquarter#i.birthyea
}
}
/* table creation code omitted */
```

6.3.1. ~~*Dockerfile*~~.

6.4. **Dockerfile.** The ~~Dockerfile~~ environment is specified through a Dockerfile. The Dockerfile in this case specifies the use of a Codeocean-specific pre-built Stata container ~~,~~as the source, injects a valid Stata license, and handles installation of any Stata packages ~~:~~ (the third method, mentioned earlier). Listing 2 shows the complete recipe, illustrating the simplicity of this approach.

Listing 2. Example Dockerfile

```
FROM registry.codeocean.com/codeocean/stata:16.0-ubuntu18.04
ARG DEBIAN_FRONTEND=noninteractive
COPY stata.lic /usr/local/stata/stata.lic
RUN stata 'ssc install estout' \
    && stata 'ssc install outreg' # Original versions: latest latest
```

6.4.1. ~~*Executing code on public (synthetic) data using commercial infrastructure*~~.

6.5. **Executing code on public (synthetic) data using commercial infrastructure.** Once the user has developed all the code, they execute a ~~"reproducible run" on CodeOcean~~"reproducible run" on Codeocean. This ensures that all code executes without error (note that it does *not* ensure that all necessary code has run - code can be commented out or be non-functional). This particular

example, when run on ~~CodeOcean~~ Codeocean infrastructure in 2021, takes about 4 minutes to execute.[22]

6.5.1. ~~*Executing code on public (synthetic) data using private or academic infrastructure*~~.

6.6. **Executing code on public (synthetic) data using private or academic infrastructure.** Alternatively, the user can export the entire capsule (including data), rebuild the image locally, and execute on their local infrastructure, using an unmodified Dockerfile. Listing 3 illustrates this process when run on an appropriately configured personal computer.

~~Note that the image built has been posted publicly at .~~

6.6.1. ~~*Validating researcher-provided code*~~. Running the actual code on the user's personal computer is then very straightforward (Listing 4).

~~Should the data custodian have doubtsabout the verified run of the capsule, or the capsule was not validated on Codeocean (because run on private infrastructure), the replicator can run the container again, using the synthetic data. This can happen in an unsecure environment, outside of the confidential dataenvironment, since no additional data requirements need to be satisfied.~~

Listing 4. Running the container

```
cd /path/to/downloaded/capsule/
docker run -it --rm \
  -v $(pwd)/code:/code \
  -v $(pwd)/data:/data \
  -v $(pwd)/results:/results \
  -w /code \
  $MYHUBID/${MYIMG} ./run
```

~~which runs for about 3 minutes on a 2021-vintage Linux workstation.~~

6.7. **Submitting code to the agency.**

6.7.1. ~~*Porting to confidential compute server*~~. Once the user is satisfied, they can submit their code to the Census Bureau, much as they are requested to do at present (U.S. Census Bureau, 2024) . Notably, they would not submit the Docker **image** built in the previous step, or provided by Codeocean, only, if modified, the Dockerfile (see Listing 5).

Listing 5. Submitted files

```
./code/00_setup.do
./code/01_stats.do
./code/02_mincer.do
./code/LICENSE
./code/README.md
./code/config.do
./code/run
./environment/Dockerfile
```

[22] Unfortunately, at the time of this writing, Codeocean does not have the ability to remove data from a published compute capsule, and the Census Bureau's current license for the SSB data does not allow to publish the synthetic data. Thus, we cannot actually point to a public instance of the compute capsule.

Listing 3. Building the container

```
cd /path/to/downloaded/capsule/environment
VERSION=16
TAG=$(date +%F)
MYHUBID=larsvilhuber
MYIMG=ssb-demo
DOCKER_BUILDKIT=1 docker build  . -t $MYHUBID/${MYIMG}:$TAG
[+] Building 5.9s (8/8) FINISHED
 => [internal] load build definition from Dockerfile
    ↪ 0.0s
 => => transferring dockerfile: 365B
    ↪ 0.0s
 => [internal] load .dockerignore
    ↪ 0.0s
[+] Building 4.5s (8/8) FINISHED
 => [internal] load build definition from Dockerfile                0.1s
 => => transferring dockerfile: 369B                                0.0s
 => [internal] load metadata for registry.codeocean.com/codeocean/s  1.1s
 => [internal] load .dockerignore                                   0.1s
 => => transferring context: 2B                                     0.0s
 => [internal] load metadata for registry.codeocean.com/codeocean/stata:1
    ↪ 0.0s
 => [internal] load build context
    ↪ 0.0s
 => => transferring context: 133B
    ↪ 0.0s
 => [1/3] FROM registry.codeocean.com/codeocean/stata:16.0-ubuntu18.04
    ↪ 0.0s
 => CACHED [2/3] COPY stata.lic /usr/local/stata/stata.lic
    ↪ 0.0s
 => [3/3] RUN stata 'ssc install estout'      && stata 'ssc install outreg
    ↪ 5.8s
 => exporting to image
    ↪ 0.0s
 => => exporting layers
    ↪ 0.0s
 => => writing image sha256:c76d3d1981c510f744cdd65e3f0c2321bc0b7a99e5285
    ↪ 0.0s
 => => naming to docker.io/larsvilhuber/ssb-demo:2022-09-11
    ↪ 0.0s
 => [internal] load build context                                   0.1s
 => => transferring context: 145B                                   0.0s
 => [1/3] FROM registry.codeocean.com/codeocean/stata:16.0-ubuntu18  0.3s
 => => resolve registry.codeocean.com/codeocean/stata:16.0-ubuntu18  0.0s
 => => sha256:fd0e31b739fe4aab4c10a61d4d0460143bb09d868fbbda6c69848  0.0s
 => => sha256:4df859214231ed09630bc2a5845a75aebdab67044dff8a2933b2e  0.0s
 => [2/3] COPY stata.lic /usr/local/stata/stata.lic                 0.1s
 => [3/3] RUN stata 'ssc install estout'      && stata 'ssc install  2.6s
 => exporting to image                                              0.1s
 => => exporting layers                                             0.1s
 => => writing image sha256:f703842568b4fac943be530a6170c953f81fc29  0.0s
 => => naming to docker.io/larsvilhuber/ssb-demo:2025-04-07         0.0s
```

The agency can do all the usual checks on the (plaintext) statistical code, and can verify if any modified Dockerfile might cause any issues. This can be done using simple tools like `diff` (Figure 4).

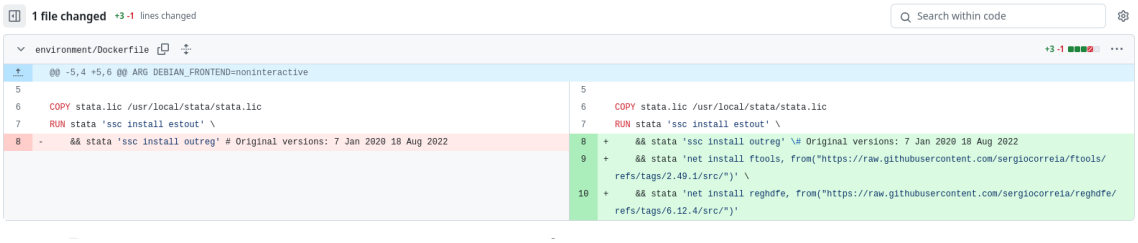

Figure 4. Checking modifications to user-provided container recipe

Importantly, all such content-based checks should be clearly identified to the users, and could be implemented during an upload process, so that efficient and rapid feedback is given to users.

6.8. **Validating researcher-provided code.** While Codeocean or other providers may confirm that the code runs reproducibly, there may be situations where the data custodians wants to separately validate reproducibility. They may have doubts, because some of the code is commented out, or any other indicator that would warrant further inspection. One possible reason is that the code was not actually validated by a commercial provider. The agency can then also run the container again, in an unsecure environment, using the synthetic data, possibly fully automated as part of the submission system. Nothing needs to pass into the secure environment for this to happen.[23]

6.9. **Porting to confidential compute server.** In order to conduct a validation exercise, the code needs to be re-executed in the secure data environment. ~~The compute capsule is~~ If the user used Codeocean and transmitted the capsule identifier, the compute capsule can be exported (via ~~"~~"Capsule -> Export~~") , which provides a full package.~~") or more likely, pulled via an API. If the user submitted code to a web interface (Listing 5), then the agency already has the code.[24] Since exporting the package is done here by the data owner, exporting the (synthetic) data is not necessary, making for a light package. ~~Alternatively, the code can also be downloaded via 'git clone' from the default CodeOcean git repository, or from a researcher's git repository. Note that it is not necessary to publish the CodeOcean capsule or to make a git repository publicly viewable, as long as it is shared with replicator.~~

6.9.1. ~~*Dynamic code provided by data custodian*~~.

6.10. **Dynamic code provided by data custodian.** As configured in the present example, the code requires only minor modifications to work on confidential data. The data custodian can provide a 'config.do' that can handle switching from synthetic to confidential for specific code pieces (Listing 6).[25]

[23] How to do this as part of open infrastructure is demonstrated at https://github.com/labordynamicsinstitute/continuous-integration-stata.

[24] In both cases, pulling the code via 'git' might also be an option.

[25] `sed -i 's/confidential no/confidential yes/' config.do` would do the trick.

Listing 6. A dynamic configuration file

```
global confidential no

/* SSB parameters */
if ( "$confidential" == "no" ) {
    global SSBtype synthetic
    global inputdata "../data"
}
if ( "$confidential" == "yes" ) {
    global SSBtype confidential
    global inputdata "/confidential/data" // This needs to be
       ↪ mounted when running the capsule!
    // other confidential parameters are stored outside of this file
    include "config-confidential.do"
}
```

Alternate methods exist as well. For instance, one could test for presence of ~~"'config-confidential.do'"~~ `config-confidential.do` and include it if present, overriding any parameters in the main ~~'config.do'~~`config.do`, or rely on environment variables. Equivalent methods exist in all programming languages.

6.11. **Modifying the container base image.** The ~~CodeOcean~~ Codeocean capsule uses a ~~CodeOcean-specific prebuilt container used to execute the code~~ Codeocean-specific prebuilt image as input to the Dockerfile (in the case of this capsule, registry.codeocean.com/codeocean/stata:16.0-ubuntu18.04). This image will need to be replaced with ~~a container~~ an image that satisfies the data ~~owner~~custodian's security requirements, while maintaining full compatibility with the needs of the environment. Because this example uses Stata, which behaves fairly uniformly across various Linux installs, the particular version of the Linux base image is likely not important. Alternatively, the validation exercise can be coordinated with the provider, and the provider can offer a generic security-vetted image that is verified to be functionally equivalent to the image used in the secure environment. Finally, the Docker file underlying the `stata:16.0-ubuntu18.04` image, which builds the container from scratch, can be used to rebuild a container within the secure environment.[26] At scale, this would simply use a similar, security-vetted, pre-built ~~container~~image available within the secure agency environment, e.g., registry.census.gov/codeocean/stata:16.0-ubuntu18.04-secure.[27]

The key feature here is that no binary code needs to be transferred into the secure environment, eliminating a substantial security risk. ~~The execution environment is completely known to the IT personnel of the data provider.~~ Only the user-provided Stata code is needed for the validation~~.~~, and a limited modification of the Dockerfile. The former is already being transferred to the agency for validation activities, and at a much larger scale within secure environments such as the FSRDCs. Only the transfer of the Dockerfile is new. Since execution is in a controlled environment, and can be trivially separated from ~~othe~~ other sensitive areas (code cannot ~~"break out"~~ "break out" of the container), security is substantially enhanced. The execution environment is completely known to the IT personnel of the data provider. Because all code should be basic ASCII or UTF-8 ~~code~~text,

[26] https://github.com/AEADataEditor/docker-stata/releases/tag/stata16-2021-06-09 for an example.

[27] This is a fake URL, no such registry currently exists.

malware or more enhanced code scanners should have no problem verifying the safety of the code. I discuss additional security considerations later.

6.11.1. ~~*Replacing the input data*~~.

6.12. **Replacing the input data.** Finally, the synthetic input data available in the public-facing environment needs to be replaced by confidential data. In the Stata code, this is already handled, as outlined above. In order to make this actionable, the Docker image can be executed in a particular fashion, provisioning the container with confidential data. Consider a directory with confidential SSB data (`$CONFDATA`) that looks like this:

```
/path/to/confidential/data:
  - ssb_v7_0_confidential1.dta
  - ssb_v7_0_confidential2.dta
  - ssb_v7_0_confidential3.dta
  - ssb_v7_0_confidential4.dta
  - ssb_v7_1_confidential1.dta
  ...
  - config-confidential.do
```

To run the provided capsule on confidential data, the confidential data directory is bind-mounted into the container, as is the configuration file for the confidential data (~~‘config-confidential.do‘~~config-confidential.do). Results are stored in a request-specific output area (here referenced by `$REQUEST`). Results are written into a `results-confidential` directory, denoting that they have not yet been vetted by data ~~provider~~custodian's disclosure avoidance procedures. All of this is under control of data custodian. Listing 7 shows how this would be implemented as a modification of Listing 4, although it is more likely to be run within an automated environment.

Listing 7. Running the container with confidential data

```
VERSION=16
TAG=16.0-ubuntu18.04-secure
MYHUBID=censusbureau
MYIMG=stata
~~STATALIC=/path/to/stata/licenses~~
CONFDATA=/path/to/confidential/data
REQUEST=12345
cd /path/to/requests
docker run -it --rm \
  ~~-v ${STATALIC}/stata.lic.${VERSION}:/usr/local/stata/stata.lic \~~
  -v $(pwd)/$REQUEST/code:/code \
  -v $(pwd)/$REQUEST/data:/data \
  -v $(pwd)/$REQUEST/results-confidential:/results \
  -v $CONFDATA/data:/confidential/data \
  -v $CONFDATA/config-confidential.do:/code/config-confidential.do \
  $MYHUBID/${MYIMG} run
```

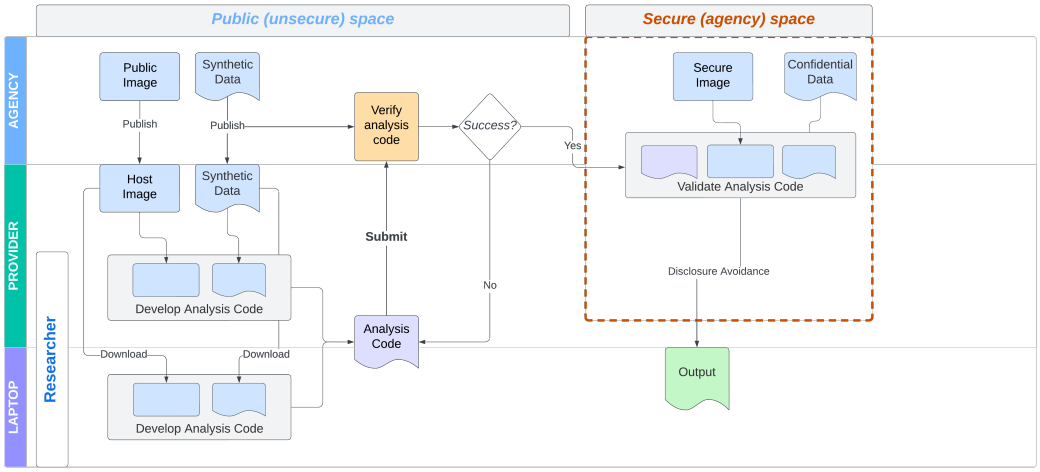

Figure 5. Sketch of a Docker-based workflow for validation of researcher code

6.12.1. ~~*Sending results back to user: output vetting*~~. However, it should be noted that the container does not have to be used for the validation. If the internal computing environment is faithfully reproduced by the container environment, then simply running the code, in combination with the `config-confidential.do`, may be sufficient. Thus, while containers are key to providing a user-facing environment, they are not a necessary condition for use within the existing secure computing environment.

6.13. **Sending results back to user: output vetting.** Once results have been generated, the usual disclosure avoidance workflow at the data provider is triggered. This might entail post-processing of the results, generation of additional supporting statistics (though these should generally be included in the processing), and finally, provision of the results to users.[28]

Figure 5 provides a simplified process flow diagram, which can be compared to Figure 1. Scalability of a system as described here hinges critically on having streamlined output vetting. Ideally, this part must also be automated. At present, non-automation of output vetting is likely the single most important bottleneck of this system. ~~Howver~~However, the challenge of creating automated and reliable disclosure avoidance procedures is not unique to the validation process described here.

6.14. **Other considerations, including additional security considerations.** For Stata (and/or R code), the security implications are no worse than those ~~currently faced by SSB Validation~~ faced by SSB and SynLBD validation using the Cornell Synthetic Data Server (until 2020), the replacement mechanism since 2024 (US Census Bureau, 2023, 2024), or in the present-day FSRDC. They are similar to those faced by other systems, such as the ~~German IAB~~ Canadian Research Data Center Network (CRDCN) or the Research Data Centre of the German Federal Employment Agency (FDZ) (Bender & Heining, 2011; Müller & vom Berge, 2021). As noted above, it should be possible to do

[28] I call this "usual", since I make no assumptions about changes to existing laws on data confidentiality that an agency is subject to. In order to be implementable, all data access, whether directly or via this new mechanism, must still be compliant with the laws that the agency is subject to, though some re-interpretation of what are permissible uses may be a separate channel to speed up access.

formal scans for malware and valid statistical code, and properly sand-boxed runs should allow for functional testing.

The example above uses `docker` as a container runtime. Docker is only one of the many container-running software environments. Some statistical agencies use `podman`. By its own documentation ~~(reference)~~("Podman", n.d.), `podman` is a full ~~"~~"drop-in~~"~~" replacement for `docker`, including the ~~"~~"`build`~~"~~" functionality illustrated earlier in this document. `podman` does not require root privileges, one of the key concerns in general with `docker`. ~~Singularity~~ Apptainer ("Apptainer - Portable, Reproducible Containers", n.d.) is also an option, used for instance in the ~~RDC~~ secure environment of the Bank of Portugal (Guimarães, 2023), and is used in many academic high-performance computing environments. Data curators administrating a validation system should choose the one that is authorized within their IT environment. The basic principles illustrated above can be ported to any one of the alternate runtimes and image stores.

In principle, we would suggest running all of the various steps (initial check for reproducibility and security issues, final validation against confidential data) in a proper isolated and sandboxed environment. There is no reason the entire process needs to interact with the statistical agency's systems at large, up until the actual validation against the confidential data.

Statistical agencies should always rebuild the ~~containers. Containers~~ base images. Images are layered (on other sites as well), allowing for the use of a properly security vetted container, running on a proper security vetted host. Some of the ~~containers~~ images demonstrated within this document are built from a ~~CodeOcean~~ Codeocean image:

```
FROM registry.codeocean.com/codeocean/stata:16.0-ubuntu18.04
```

but can just as easily be created from a base image ~~maintained by one of the authors~~ I maintain with full transparency:

```
ARG SRCVERSION=17
ARG SRCTAG=2022-01-17
ARG SRCHUBID=dataeditors
FROM ${SRCHUBID}/stata${SRCVERSION}:${SRCTAG}
```

The use of a (currently nonexistent) **public** Census-sanctioned image might be used for the first step:

```
FROM registry-public.census.gov/validation/stata:17.0-rh-secure-
    ↪ public
```

and would simply be replaced by an equivalent but fully security compliant internal image when rebuilding the image in the confidential environment:

```
FROM registry.census.gov/validation/stata:17.0-rh-secure-internal
```

6.14.1. ~~*Scalability*~~.

6.15. **Scalability.** For users to accept the restrictions of the synthetic data, it should scale better. So many of the vetting/building/running parts should (can easily) be streamlined. One key piece missing: standardized/streamlined output vetting.

6.15.1. ~~*Data licensing*~~.

6.16. **Data licensing.** One key condition for such a system is the ability to post ~~SSB~~ synthetic data publicly, albeit classified and published as ~~"~~"experimental data.~~" ~~"~~ In contrast to the Cornell (or any other) Synthetic Data Server, the public component of the system would no longer have control over dissemination of the synthetic data files, but continue to have control over validation.[29]

As an added benefit, by compiling a library of container-based scientific uses of a particular dataset, the data provider can test out new data releases, alternative disclosure avoidance methods, or replacement data sources at scale against prior scientific findings. This is currently not (easily) feasible - most such re-validations are painstakingly manual, and limited in scale, as noted earlier. The benefit would be improved user input on new and novel methods and data.

7. ~~Conclusion~~Discussion

~~The use of containers~~

7.1. **Returning to the desiderata.** Containers satisfy most of the desiderata outlined earlier: [D1] the Docker-based mechanism supports arbitrary modeling approaches, and in principle a large number of programming languages (modulo what the agency allows) ; [D2] the Docker-based mechanism allows for development of models by researchers on their personal computer, if necessary, as long as they subsequently test their model within the prescribed Docker-based mechanism themselves ; [D3] the mechanism is low-cost (or even at no cost) for the data provider, and can be scaled up effectively; the costs are born by the compute providers (and possibly charged to the user) ; [D4] the mechanism can be low-cost for the data user: Most current cloud computing solutions that support this are at a trivial cost to the data user, and may be born by their institution (academic or otherwise). Alternatively, development on their own personal computer imposes no additional cost ; [D5] current privacy-protected data (SynLBD, SSB) are good enough to allow for complex modeling, and the low-cost nature of the validation process allows for the development of additional synthetic data releases that trade off statistical accuracy for modeling utility, which is likely to be much simpler , and [D6] validation can be technically fast, albeit with a caveat.

7.2. **Some caveats.** Two caveats are in order. First, [D5] is contingent on finding an acceptable mechanism to rapidly generate useful synthetic data, possibly model-dependent. Tools for that exist (Nowok, Raab, & Dibben, 2016; Nowok, Raab, Snoke, & Dibben, 2016), and the disclosure-avoidance analysis is improving (Snoke et al., 2016). However, in order for validation not just to be fast to process, but also fast to release to the user ([D6]), agencies need to accept and deploy privacy-protection mechanism that can scale. Current mechanisms in restricted-access data centers (FSRDC, CRDCN, FDZ) are often manual (Brandt et al., 2010), albeit first attempts at using large language models (LLMs) to speed up the process are being actively developed (Rigaud et al., 2023).

7.3. **Addressing implementation issues.** While much of the technology is straightforward "off-the-rack" technology, the fact that it is not being used by statistical agencies or survey institutes suggests that some training is required and guidelines for deployment needed. (1) Guidelines for agencies on how to prepare container specifications reflective of their internal execution environment, taking into account industry best practices on container specifications, security considerations, and usability are a necessity. NIST has some guidelines (Souppaya et al., 2017), and guidelines for secure use of containers for applications abound, and can be easily adapted to internal use at agencies. What

[29] I do note that the European concept of a "scientific use file" does allow for controlled dissemination to certified educational institutions.

is less available are guidelines on how to publish such containers for public consumption, these will likely need to be developed, possibly in conjunction with the target audience. (2) Users may need some guidance on general use of containers, and how to use containers in conjunction with this mechanism. There are many training documents and class notes available for general use of containers (Boettiger, 2015; Eyers et al., 2020; McDermott, 2023; Nüst, 2017; The Turing Way Community, 2024; Vilh , but few of them are actually known to most (academic) social scientists. How to use this specifically for the purpose of validation may need some training, though I suspect less so then the use of an idiosyncratic desktop platform that is even less familiar to users, as the SDS was. Financial incentives might be used for a pilot phase.

7.4. **How do we know it works?** The premise of my proposal is that it is easier and cheaper to implement. At present, the creation of highly protective synthetic data, and the supporting infrastructure for validation, is complex and therefore expensive.[30] How would we know if this is cheaper? Implementing agencies could track how much time was spent on submissions that were submitted with manual validation, how much time is spent managing complex data access protocols (when researchers themselves need to access the confidential data), and compare that to automated submissions under the current proposal (ideally in a randomized experiment), allowing an assessment of the first-order impact on costs at the agency. Other cost factors might apply as well, for instance if the agency does not currently use containers, implementation costs of deploying software to manage submissions in such an automated way. IT personnel hopefully is aware of what it means to run containers within a large organization, but may need to adapt it to the particular research environment. Non-pecuniary metrics might include the increase in usage of datasets, as well as in the number of validation requests. Second-order cost increases through expanded use remain hard to measure, and would need to be assessed in a broader cost-benefit analysis. Security and cost considerations might also affect the allowable set of software that can be used in containers, though it is an open question whether restricting users to specific software packages truly is an impediment to data use.[31]

7.5. **Possible extensions to more complex frameworks.** A critical bottleneck is disclosure avoidance, in part because the traditional analysis methods (both of public-use data and of synthetic data) are disclosure-avoidance agnostic, i.e., they do not incorporate prior or subsequent disclosure avoidance measures into the analysis method (Abowd & Schmutte, 2015). A first step is to include in the analysis container methods and metrics that allow users to assess how subsequent disclosure avoidance metrics will impact the releasable tables (Reiter, 2010). For instance, prepared methods to apply traditional disclosure methods to the designated outputs (aggregation, suppression, rounding, see Brandt et al., can be incorporated into the container. The SDS already allowed to assess inference when combining estimates from multiple synthetic datasets (the SSB provides four implicates).

Applying methods that incorporate diffential privacy directly into the analysis methods (Alabi & Vadhan, 2022; Alabi still provide incomplete coverage of the analysis methods used by social scientists (see Barrientos et al., 2021, for an overv

[30] The SDS was supported by Sloan Foundation and National Science Foundation (NSF) grants as well as Census Bureau staff time over more than a decade, and the aforementioned project for synthetic IRS data is supported through grants by the Sloan Foundation, each of which was typically a multi-year project with cumulatively several million dollar support.

[31] Observationally, the usage of SAS in the broader academic community in the social sciences is approximately zero, yet many replication packages that are associated with FSRDC or CRDCN projects still contain SAS code.

. A promising but still preliminary system at this time is the IRS synthetic data file (Burman et al., 2018; Tyagi et al., 20
. Whether such a system can be implemented with a simple container-based approach as outlined here remains to be seen.

8. In conclusion

The use of containers for validation of analyses that were prepared using synthetic data ensures reproducibility, reliable portability, and enables scalability. The use of cloud-based commercial or university-based services requires no infrastructure or software maintenance by either data provider or users, ~~but is not a necessary condition, as users can easily provide their own infrastructure~~and often no direct cost. With very little effort, automation is possible (potentially through web forms), and the only likely ~~constraint to full automation is the absence of automated output vetting algorithms.~~

~~Thus, containers satisfy most of the desiderate outlined earlier, but still rely on high-quality synthetic data, and a~~ If privacy-protection ~~mechanism that can scale. If such a privacy-protection mechanism~~ mechanisms can be tuned to acceptable protection levels (on par with traditional mechanisms that are applied to unrestricted public-use products), then validation can be made highly automated, and the quality of the synthetic data itself can be decreased, while maintaining high levels of user acceptance due to a fast validation process.

~~**Disclosure Statement.** The author have~~

Disclosure Statement

The author has no conflicts of interest to declare. The mention of commercial entities is not meant to endorse any such providers, and the author holds no financial interest in any of the mentioned commercial entities.

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~~**Contributions.**~~

Contributions

LV conceived the topic, wrote the text, and prepared the examples. The statistical code used within the container, serving as a stand-in for any statistical analysis, was provided by Evan Totty, U.S. Census Bureau.

References

Abowd, J. M., Ashmead, R., Cumings-Menon, R., Garfinkel, S., Heineck, M., Heiss, C., Johns, R., Kifer, D., Leclerc, P., Machanavajjhala, A., Moran, B., Sexton, W., Spence, M., & Zhuravlev, P. (2022, April). The 2020 Census Disclosure Avoidance System TopDown Algorithm [arXiv:2204.08986 [cs, econ, stat]]. https://doi.org/10.48550/arXiv.2204.08986

Abowd, J. M., & Schmutte, I. (2015). Economic analysis and statistical disclosure limitation [tex.copyright: Copyright © 2015 Brookings Institution Press tex.jstor_articletype: research-article tex.publisher: Brookings Institution Press]. *Brookings Papers on Economic Activity*, *Fall 2015*. http://www.brookings.edu/about/projects/bpea/papers/2015/economic-analysis-statistical-disclosure-limitation

Alabi, D., McMillan, A., Sarathy, J., Smith, A., & Vadhan, S. (2020, July). Differentially Private Simple Linear Regression [arXiv:2007.05157 [cs, stat]]. Retrieved February 8, 2023, from http://arxiv.org/abs/2007.05157

Alabi, D., & Vadhan, S. (2022). *Hypothesis testing for differentially private linear regression* (arXiv No. 2206.14449) (tex.copyright: arXiv.org perpetual, non-exclusive license). arXiv. https://doi.org/10.48550/ARXIV.2206.14449

Alabi, D., & Vadhan, S. P. (2023). Differentially Private Hypothesis Testing for Linear Regression. *Journal of Machine Learning Research*, *24*, 1–50. https://jmlr.org/papers/v24/23-0045.html

Allaire, J., Teague, C., Scheidegger, C., Xie, Y., Dervieux, C., & Woodhull, G. (2024, November). *Quarto* (Version 1.6). https://doi.org/10.5281/zenodo.5960048

American Economic Association. (2016). *Allied Social Science Associations Program* (Program No. 2016). American Economic Association. San Francisco. Retrieved July 10, 2024, from https://assets.aeaweb.org/asset-server/files/815.pdf

Apptainer - Portable, Reproducible Containers. (n.d.). Retrieved April 3, 2025, from https://apptainer.org/

Armour, P., Burkhauser, R. V., & Larrimore, J. (2016). Using the Pareto distribution to improve estimates of topcoded earnings. *Economic Inquiry*, *54*(2), 1263–1273. https://doi.org/10.1111/ecin.12299

Association for Computing Machinery. (2003). ACM Software System Award: Stuart Feldman. Retrieved April 4, 2025, from https://awards.acm.org/award-recipients/feldman_1240498

Barrientos, A. F., Bolton, A., Balmat, T., Reiter, J. P., de Figueiredo, J. M., Machanavajjhala, A., Chen, Y., Kneifel, C., & DeLong, M. (2018). Providing Access to Confidential Research Data Through Synthesis and Verification: An Application to Data on Employees of the U.S. Federal Government [arXiv: 1705.07872]. *The Annals of Applied Statistics*. Retrieved March 12, 2020, from http://arxiv.org/abs/1705.07872

Barrientos, A. F., Williams, A. R., Snoke, J., & Bowen, C. (2021, November). *Differentially Private Methods for Validation Servers: A Feasibility Study on Administrative Tax Data* (tech. rep.). Urban Institute. Retrieved April 9, 2025, from https://www.urban.org/research/publication/differentially-private-methods-validation-servers

Bender, S., & Heining, J. (2011). *The Research-Data-Centre in Research-Data-Centre approach: A first step towards decentralised international data sharing* (FDZ Methodenreport No. 07/2011 (en)). Retrieved October 5, 2020, from http://doku.iab.de/fdz/reporte/2011/MR_07-11_EN.pdf

Benedetto, G., Stinson, M., & Abowd, J. M. (2013). *The creation and use of the SIPP Synthetic Beta* (tech. rep.) (tex.timestamp: 2015.02.11). US Census Bureau. http://www.census.gov/content/dam/Census/programs-surveys/sipp/methodology/SSBdescribe_nontechnical.pdf

Boettiger, C. (2015). An introduction to Docker for reproducible research. *ACM SIGOPS Operating Systems Review*, *49*(1), 71–79. https://doi.org/10.1145/2723872.2723882

Brandt, M., Franconi, L., Guerke, C., Hundepool, A., Lucarelli, M., Mol, J., Ritchie, F., Seri, G., & Welpton, R. (2010, January). *Guidelines for the checking of output based on microdata research* (tech. rep.). Retrieved April 9, 2025, from https://uwe-repository.worktribe.com/output/983615/guidelines-for-the-checking-of-output-based-on-microdata-research

Brinckman, A., Chard, K., Gaffney, N., Hategan, M., Jones, M. B., Kowalik, K., Kulasekaran, S., Ludäscher, B., Mecum, B. D., Nabrzyski, J., Stodden, V., Taylor, I. J., Turk, M. J., & Turner, K. (2018). Computing environments for reproducibility: Capturing the "Whole Tale". *Future Generation Computer Systems*. https://doi.org/10.1016/j.future.2017.12.029

Burman, L. E., Engler, A., Khitatrakun, S., Nunns, J. R., Armstrong, S., Iselin, J., MacDonald, G., & Stallworth, P. (2018). *Administrative tax data: Creating a synthetic public use file and a validation server* (document). Tax Policy Center, Urban Institute and Brookings Institution. https://www.urban.org/research/publication/safely-expanding-research-access-administrative-tax-data-creating-synthetic-public-use-file-and-validation-server

Chard, K., Gaffney, N., Hategan, M., Kowalik, K., Ludaescher, B., McPhillips, T., Nabrzyski, J., Stodden, V., Taylor, I., Thelen, T., Turk, M. J., & Willis, C. (2020). Toward Enabling Reproducibility for Data-Intensive Research using the Whole Tale Platform [arXiv: 2005.06087]. *arXiv:2005.06087 [cs]*. https://doi.org/10.3233/APC200107

Chaudhuri, K., & Monteleoni, C. (2008). Privacy-preserving logistic regression. *Advances in Neural Information Processing Systems*, *21*. Retrieved April 9, 2025, from https://proceedings.neurips.cc/paper_files/paper/2008/hash/8065d07da4a77621450aa84fee5656d9-Abstract.html

Clyburne-Sherin, A., Fei, X., & Green, S. A. (2019). Computational Reproducibility via Containers in Psychology. *Meta-Psychology*, *3*. https://doi.org/10.15626/MP.2018.892

Contributors to the Apptainer project. (2025). Apptainer - Portable, Reproducible Containers. Retrieved April 3, 2025, from https://apptainer.org/

Daily, D. (2022, December). *Disclosure Avoidance Protections for the American Community Survey* (Blog post). US Census Bureau. Retrieved July 8, 2024, from https://www.census.gov/newsroom/blogs/random-samplings/2022/12/disclosure-avoidance-protections-acs.html

Donoho, D. (2024). Data Science at the Singularity. *Harvard Data Science Review*, *6*(1). https://doi.org/10.1162/99608f92.b91339ef

Drechsler, J. (2021). Differential Privacy for Government Agencies – Are We There Yet? *arXiv:2102.08847 [cs, stat]*. Retrieved February 24, 2021, from http://arxiv.org/abs/2102.08847

Drechsler, J., & Haensch, A.-C. (2024). 30 Years of Synthetic Data. *Statistical Science*, *39*(2). https://doi.org/10.1214/24-STS927

Eyers, D. M., Stevens, S. L. R., Turner, A., Koch, C., & Cohen, J. (2020). Reproducible Computational Environments Using Containers. Retrieved April 9, 2025, from https://carpentries-incubator.github.io/docker-introduction/

Guimarães, P. (2023). Reproducibility With Confidential Data: The Experience of BPLIM. *Harvard Data Science Review*, *5*(3). https://doi.org/10.1162/99608f92.54a00239

Heckman, J., Lochner, L., & Todd, P. (2003, May). *Fifty Years of Mincer Earnings Regressions* (working paper No. w9732). National Bureau of Economic Research. Cambridge, MA. https://doi.org/10.3386/w9732

Herbert, S., Kingi, H., Stanchi, F., & Vilhuber, L. (2024). Reproduce to validate: A comprehensive study on the reproducibility of economics research. *Canadian Journal of Economics/Revue canadienne d'économique*, caje.12728. https://doi.org/10.1111/caje.12728

Karr, A. F., Kohnen, C. N., Oganian, A., Reiter, J. P., & Sanil, A. P. (2006). A framework for evaluating the utility of data altered to protect confidentiality. *The American Statistician*, *60*(3), 1–9. https://doi.org/10.1198/000313006X124640

Kinney, S. K., Reiter, J. P., Reznek, A. P., Miranda, J., Jarmin, R. S., & Abowd, J. M. (2011). Towards unrestricted public use business microdata: The synthetic longitudinal business database [tex.owner: vilhuber tex.publisher: Blackwell Publishing Ltd tex.timestamp: 2012.09.04]. *International Statistical Review*, *79*(3), 362–384. https://doi.org/10.1111/j.1751-5823.2011.00153.x

Leisch, F. (2002). Sweave: Dynamic generation of statistical reports using literate data analysis. *International Conference on Computational Statistics*. https://link.springer.com/chapter/10.1007/978-3-642-57489-4_89

Liberman, M. (2010). Obituary: Fred Jelinek. *Computational Linguistics*, *36*(4), 595–599. https://doi.org/10.1162/coli_a_00032

Liberman, M. (2014, December). Reproducible Research and the Common Task Method. Retrieved April 3, 2025, from https://www.simonsfoundation.org/event/reproducible-research-and-the-common-task-method/

Little, R. J. (1993). Statistical analysis of masked data. *Journal of Official Statistics*, *9*(2), 407–426.

Liu, D. M., & Salganik, M. J. (2019). Successes and Struggles with Computational Reproducibility: Lessons from the Fragile Families Challenge. *Socius*, *5*, 2378023119849803. https://doi.org/10.1177/2378023119849803

McDermott, G. (2023). Data Science for Economists. Retrieved April 9, 2025, from https://github.com/uo-ec607/lectures

Meng, X.-L. (1994). Multiple-imputation inferences with uncongenial sources of input. *Statistical Science*, *9*(4), 538–558. http://www.jstor.org/stable/2246252

Mincer, J. (1984). *Schooling, experience, and earnings*. Columbia University Press.

Mölder, F., Jablonski, K. P., Letcher, B., Hall, M. B., Tomkins-Tinch, C. H., Sochat, V., Forster, J., Lee, S., Twardziok, S. O., Kanitz, A., Wilm, A., Holtgrewe, M., Rahmann, S., Nahnsen, S., & Köster, J. (2021, January). Sustainable data analysis with Snakemake. https://doi.org/10.12688/f1000research.29032.1

Moreau, D., Wiebels, K., & Boettiger, C. (2023). Containers for computational reproducibility. *Nature Reviews Methods Primers*, *3*(1), 1–16. https://doi.org/10.1038/s43586-023-00236-9

Müller, D., & vom Berge, P. (2021, January). Institute for Employment Research, Germany: International Access to Labor Market Data. In S. Cole, I. Dhaliwal, A. Sautmann, & L. Vilhuber (Eds.), *Handbook on Using Administrative Data for Research and Evidence-based Policy*. Abdul Latif Jameel Poverty Action Lab. https://doi.org/10.31485/admindatahandbook.1.0

Nowok, B., Raab, G. M., & Dibben, C. (2016). Synthpop : Bespoke creation of synthetic data in R [tex.owner: vilhuber tex.timestamp: 2017.07.04]. *Journal of Statistical Software*, *74*, 1–26. https:%20//www.jstatsoft.org/article/view/v074i11

Nowok, B., Raab, G. M., & Dibben, C. (2017). Providing bespoke synthetic data for the UK Longitudinal Studies and other sensitive data with the synthpop package for R1. *Statistical Journal of the IAOS*, *33*(3), 785–796. https://doi.org/10.3233/SJI-150153

Nowok, B., Raab, G. M., Snoke, J., & Dibben, C. (2016). *Synthpop: Generating synthetic versions of sensitive microdata for statistical disclosure control*. https://CRAN.R-project.org/package=synthpop

Nüst, D. (2017, July). Automatically archiving reproducible studies with Docker. https://doi.org/10.5281/zenodo.824007

Podman. (n.d.). Retrieved April 6, 2025, from https://podman.io/

Raghunathan, T. (2021). Synthetic Data. *Annual Review of Statistics and Its Application*, *8*(1), null. https://doi.org/10.1146/annurev-statistics-040720-031848

Raghunathan, T., & Chaney, B. (Eds.). (2023). *A Roadmap for Disclosure Avoidance in the Survey of Income and Program Participation* [Pages: 27169]. National Academies Press. https://doi.org/10.17226/27169

Raghunathan, T., & Hotz, V. J. (2024). *A roadmap for disclosure avoidance in the survey of income and program participation sipp* (Presentation). NBER.

Reeder, L. B., Stanley, J. C., & Vilhuber, L. (2018). *Codebook for the SIPP Synthetic Beta v7.0 [Codebook file]* (DDI-C document). Cornell Institute for Social, Economic Research, and Labor Dynamics Institute [distributor]. Cornell University. Ithaca, NY, USA. http://www2.ncrn.cornell.edu/ced2ar-web/codebooks/ssb/v/v7

Reiter, J. P. (2010). Multiple imputation for disclosure limitation: Future research challenges [tex.owner: vilhuber tex.timestamp: 2017.07.04]. *Journal of Privacy and Confidentiality*, *1*(2). http://repository.cmu.edu/jpc/vol1/iss2/7

Reiter, J. P. (2023). Synthetic Data: A Look Back and A Look Forward. *Transactions on Data Privacy*, *16*(1). http://www.tdp.cat/issues21/tdp.a457a22.pdf

Reiter, J. P., Oganian, A., & Karr, A. F. (2009). Verification servers: Enabling analysts to assess the quality of inferences from public use data. *Computational statistics & data analysis*, *53*(4), 1475–1482. https://doi.org/10.1016/j.csda.2008.10.006

Rigaud, T., Marquier, R., Debonnel, E., & Liu, P. (2023). Checking data outputs from research works: A mixed method with ai and human control. *United Nations Economic Commission for Europe (UNECE) Conference of European Statisticians (CES): Expert meeting on Statistical Data Confidentiality*, 26–28. Retrieved April 9, 2025, from https://scholar.google.com/scholar?cluster=9376666103583018923&hl=en&oi=scholarr

Rubin, D. B. (1993). Discussion: Statistical disclosure limitation. *Journal of Official Statistics*, *9*(2), 461–468. https://www.scb.se/contentassets/ca21efb41fee47d293bbee5bf7be7fb3/discussion-statistical-disclosure-limitation2.pdf

Sheffet, O. (2019). Differentially Private Ordinary Least Squares [Number: 1]. *Journal of Privacy and Confidentiality*, *9*(1). https://doi.org/10.29012/jpc.654

Snoke, J., Raab, G., Nowok, B., Dibben, C., & Slavkovic, A. (2016). General and specific utility measures for synthetic data [arXiv: 1604.06651v2 [stat.AP] tex.__markedentry: [vilhuber:] tex.owner: vilhuber tex.timestamp: 2017.07.04].

Souppaya, M., Morello, J., & Scarfone, K. (2017, September). *Application container security guide* (tech. rep. No. NIST SP 800-190). National Institute of Standards and Technology. Gaithersburg, MD. https://doi.org/10.6028/NIST.SP.800-190

Stockemer, D., Koehler, S., & Lentz, T. (2018). Data Access, Transparency, and Replication: New Insights from the Political Behavior Literature. *PS: Political Science & Politics*, *51*(4), 799–803. https://doi.org/10.1017/S1049096518000926

Stodden, V., Seiler, J., & Ma, Z. (2018). An empirical analysis of journal policy effectiveness for computational reproducibility. *Proceedings of the National Academy of Sciences*, 201708290. https://doi.org/10.1073/pnas.1708290115

The FreeBSD Project. (2025, March). Chapter 17. Jails and Containers. Retrieved April 3, 2025, from https://docs.freebsd.org/en/books/handbook/jails/

The Turing Way Community. (2024). Containers. Retrieved April 9, 2025, from https://book.the-turing-way.org/reproducible-research/renv/renv-containers

Tyagi, E., Taylor, S., MacDonald, G., Tamaroff, D., Miller, J., Williams, A. R., & Bowen, C. (2024, September). *A Privacy-Preserving Validation Server Version 2.0: Technical White Paper for an Automated Validation Server Prototype* (tech. rep.). Urban Institute. Retrieved April 9, 2025, from https://www.urban.org/research/publication/privacy-preserving-validation-server-version-2

U.S. Census Bureau. (2011). *Synthetic LBD Beta Version 2.0* ([Computer file]) (Published: Computer file). Cornell University, Synthetic Data Server [distributor]. Washington,DC, Ithaca, NY, USA. http://www2.vrdc.cornell.edu/news/data/lbd-synthetic-data/

U.S. Census Bureau. (2015a). *SIPP Synthetic Beta Version 7.0* ([Computer file]) (Published: Computer file). Cornell University, Synthetic Data Server [distributor]. Washington,DC, Ithaca, NY, USA. http://www2.vrdc.cornell.edu/news/data/sipp-synthetic-beta-file/

U.S. Census Bureau. (2015b, January). *Disclosure Review Board Memo: Second Request for Release of SIPP Synthetic Beta Version 6.0* (tech. rep.). U.S. Census Bureau. http://hdl.handle.net/1813/42334

US Census Bureau. (2023). Validating Results - Synthetic LBD. Retrieved April 6, 2025, from https://www.census.gov/programs-surveys/ces/data/public-use-data/synthetic-longitudinal-business-database/validating-results.html

U.S. Census Bureau. (2024). *SIPP Synthetic Beta Version 7.0* ([Computer File]). U.S. Census Bureau [distributor]. Washington, DC, USA. https://www.census.gov/programs-surveys/sipp/guidance/sipp-synthetic-beta-data-product.html
Published: Computer file.

Vilhuber, L. (2013). *Codebook for the Synthetic LBD Version 2.0 [Codebook file]* (DDI-C document). Comprehensive Extensible Data Documentation, Access Repository (CED2AR), Cornell Institute for Social, Economic Research, and Labor Dynamics Institute [distributor]. Cornell University. Ithaca, NY, USA. http://www2.ncrn.cornell.edu/ced2ar-web/codebooks/synlbd/v/v2

Vilhuber, L. (2021, November). Use of Docker for Reproducibility in Economics. Retrieved January 3, 2022, from https://aeadataeditor.github.io/posts/2021-11-16-docker

Vilhuber, L. (2024). *Aeadataeditor/docker-stata* (repository). Github. https://github.com/AEADataEditor/docker-stata

Vilhuber, L., & Abowd, J. M. (2022, July). *End of life for the Cornell Synthetic Data Server September 30, 2022* (Blog post). Cornell University. https://web.archive.org/web/20221130032540/https://www2.vrdc.cornell.edu/news/

Vilhuber, L., & Cavanagh, J. (2025). Report by the AEA Data Editor. *AEA Papers and Proceedings*, *115*, xxx–xxx. https://doi.org/10.1257/pandp.115.xxx

Vilhuber, L., Turitto, J., & Welch, K. (2020). Report by the AEA Data Editor. *AEA Papers and Proceedings*, *110*, 764–75. https://doi.org/10.1257/pandp.110.764

Responses

General responses

Response: Thank you to the editor and the reviewers for their valuable input, which I very much appreciated, and which I believe has lead to substantial improvement of the text. I have revised the structure of the text, and linked it with various other efforts highlighted by the reviewers.

- I have added a new introduction that lays out what the article intends to convey, and what tools it will describe. This should help make it clearer from the start, and should have been included; my apologies for only adding it now.
- I then follow with a section that describes and situates the various concepts, both those that might be new to some in the readership ("containers") and those that might be known, but possibly ambiguously defined and used in a broader context (first among them: "synthetic data"). This was a request by multiple reviewers, suggesting that it is still a necessary structure to provide. I will note that I had previously talked with others in the open (social) science field, who very much implied that even the late definition of containers was "very pedantic" because apparently everybody (should) know about that by now... highlighting the wide diversity in information dispersal even within the narrow "field" of social science. I hope that the current definitions strike a good balance.
- I have also replaced Figure 1 with a better figure, referenced it in the text, and added Figure 5, which shows the equivalent process flow for the Docker-based approach. For reference, here are the old Figure 1 and the new Figure 1 side-by-side (Figure 6.

- I have also linked the various code fragments more closely to the text, explaining in more detail what they do, for those not necessarily familiar with the code. I have also corrected a few inaccuracies not noted by the referees when describing the setup of the container in the example. A link to a complete online example is provided.

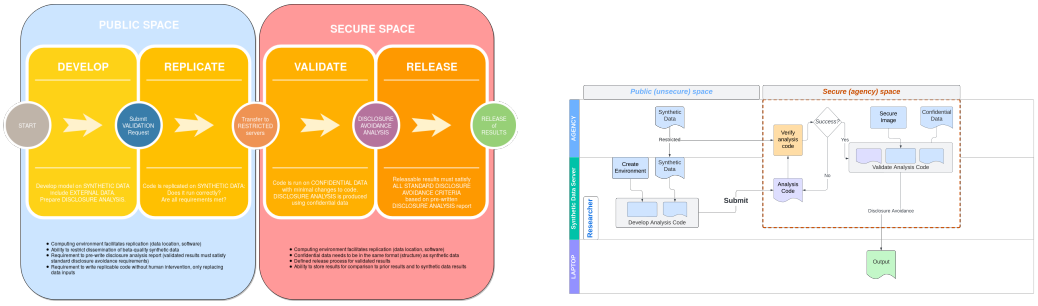

Figure 6. Old and new Figure 1

To editor

As you can see from the three reports attached, the reviewers are generally positive about the topic, but have a number of non-trivial concerns and suggestions on the substance (especially from Reviewer 1) and on the paper organization and presentation. Reading it myself I can see why Reviewers 2 and 3 find it difficult to see quickly what the article is about. I surmise the concept of "container" is not a commonly understood one, and even after I read its description in Section 5, it is not immediately intuitive why it can protect data privacy at scale. Of course that reflects my ignorance, and your article is to educate people like me. Although I am of sample size 1, I'm quite confident that over 50% of statisticians are as clueless as I am on this topic. :-) For people like me, the article would be much more enticing if it starts with defining the container, and explain it intuitively in what ways it helps to protect data privacy, and can do so at scale. Then you can discuss why other methods are inferior and in what way.

Response: I have now added a new introduction that lays out the goal of the article, and then added/reformated a section on concepts and prior science, which should hopefully address this point.

By the way, the list of desiderata in Section 6 is great, but I am a strong believer of the no-free lunch principle. I'd be very happy to be wrong here, but suspect in many practical situations, one may need to prioritize some. If so, some discussions on how to prioritize may make readers pay more attention to the list, as those who find the list too demanding or idealistic might choose to ignore it.

Response: This was actually, somewhat obliquely and apparently not clearly, included in the Conclusion:

> Thus, containers satisfy most of the desiderata outlined earlier, but still rely on high-quality synthetic data, and a privacy-protection mechanism that can scale.

I address this (hopefully) better in an greatly expanded conclusion/discussion, where I also address many of Reviewer 1's excellent points.

Reviewer 1:

The manuscript centers on the use of container technology to improve access to confidential data for research while ensuring data privacy and security. The manuscript outlines how containers, in combination with synthetic data and controlled environments like Codeocean, provide researchers and data stewards with a compatible setup that facilitates statistical analysis on confidential datasets while preserving privacy. The manuscript discusses how containers create reproducible, secure environments that can be deployed on public or private infrastructure, enabling researchers to develop and validate code on synthetic data. Once validated, this code can be securely transferred to confidential environments for final analysis. The manuscript emphasizes the scalability, reproducibility, and importance of disclosure avoidance procedures enabled by containers, ensuring sensitive information remains protected throughout the research process. It also acknowledges that, although the use of containers helps mitigate scalability issues, a major bottleneck in scaling this system will still lie in the need for automated output vetting, which remains a key challenge in disclosure avoidance.

Response: Thank you for the succinct summary, which is better than mine! I have expanded the intro, and included a summary which I hope is as inteligible as yours.

The manuscript presents a strong case for using containers to improve access to confidential datasets while preserving privacy. By using containerization, the approach enhances reproducibility through a standardized environment as researchers can conduct analyses within consistent configurations. This setup enables data stewards to establish clear boundaries, such as specific software versions and dependencies, which helps ensure a controlled and reproducible workflow. Managing these parameters creates an environment where analyses can be reliably repeated or validated. The approach aligns well with best practices in secure data handling. The requirement for researchers to provide only their code, combined with the container's capacity to be rebuilt within a secure environment, adds efficiency to the process. An implementation of this idea by an institution committed to providing access to confidential datasets while safeguarding privacy would be valuable.

Response: Thank you for that. I hope you are also the reviewer for our grant application.

Below are some suggestions to further strengthen the manuscript.
A valuable addition to the manuscript would be a subsection (or adding some paragraphs) discussing metrics that institutions might consider when evaluating the feasibility of container-based secure environments for accessing and analyzing confidential datasets. Some potential metrics could be:

- *Hardware and infrastructure costs associated with supporting container technology, especially if large datasets or complex analyses require substantial computational resources.*
- *Number of validations that can be completed in a given period of time, such as per week.*
- *IT personnel costs, as institutions will likely need staff skilled in containerization, data security, and privacy protocols to set up and maintain these environments effectively.*
- *Learning costs for both internal and external users, including the time and resources required to train users unfamiliar with container technology.*
- *The types of software, programming languages, and analysis tools that potential users currently rely on. This information, possibly gathered through a user survey, can guide institutions in configuring containers with compatible software and dependencies. However, institutions may face challenges in surveying a representative sample of potential users.*

Response: Thank you for that suggestion. We did actually include the first two of those metrics in our grant application, and **I have expanded what was previously called a Conclusion** (somewhat presumptively), which is now **Discussion**, discussing the desiderata (as requested by the Editor) and these metrics. While I don't (here) expound on the survey for required tools, I do mention that institutions should be aware of the tools being used in the community that they serve, for instance by looking at the distribution of software used in replication packages. I do point out that it might not be so constraining, using the example of SAS. There is almost no SAS usage left on university campuses, at least in the social sciences, yet many replication packages that contain code run in government research data centers still contain SAS. Researchers are willing to learn new software if it gives them access to data.

Compliance with relevant laws.

Response: I did not address this issue explicitly, because I assumed that no laws need to be changed in order to implement this mechanism. I did add a footnote, identifying this assumption, when discussing disclosure avoidance.

> Footnote: I call this "usual", since I make no assumptions about changes to existing laws on data confidentiality that an agency is subject to. In order to be implementable, all data access, whether directly or via this new mechanism, must still be compliant with the laws that the agency is subject to, though some re-interpretation of what are permissible uses may be a separate channel to speed up access.

The code snippets provided in the document are a valuable addition, moving the discussion from theory to application and giving readers actionable steps to set up their containerized environments. This hands-on approach makes the concept more accessible, especially for those looking to replicate or test the methods described. To further enhance clarity, it would be beneficial to include more inline comments within the code snippets to explain relevant lines, particularly for readers unfamiliar with Dockerfile syntax and Stata commands.

Response: This is a good point, though I subject this to the Editor's filter of how long an article should be. I now explicitly link to the Github repository with the complete example, and have added comments there, as a hopefully acceptable compromise.

The distinction between "reproducible run" and "validating researcher-provided code" in Sections 6.3.2 and 6.3.4 could benefit from further clarification, as these terms may seem similar yet serve distinct purposes. In Section 6.3.2, the term "reproducible run" appears to refer to an initial execution of code on CodeOcean's infrastructure to confirm that the code runs without technical errors though this does not guarantee that all necessary code has been executed, as sections of code may be commented out or non-functional. In contrast, Section 6.3.4 describes a "validation" step where the replicator, or data custodian, re-runs the container on synthetic data to ensure reproducibility in a non-secure environment if there are any doubts or if initial validation wasn't completed on CodeOcean. While someone with a computer science background might quickly understand these nuances, broader audiences might find the distinction confusing. For this reason, it would be beneficial for the manuscript to elaborate on these two steps, clarifying their distinct roles in the reproducibility and validation process.

Response: I have expanded this discussion somewhat in the text, hopefully to the reviewer's satisfaction.

The document could benefit from addressing ongoing developments in the use of validation servers, particularly those leveraging differential privacy to automate output vetting. Several research organizations are exploring validation servers because they allow institutions to control how users submit queries and specify the types of output that can be released, facilitating integration with differential privacy. Implementing a similar approach with containers raises interesting possibilities and potential challenges. For example, it could be feasible to set up containers equipped with OpenDP, enabling users to run analyses with differential privacy settings on synthetic data. This setup could allow users to test analyses within a "reasonable" privacy budget and compare the outputs against those obtained using standard statistical software that does not employ differential privacy. However, with the proposed approach based on container technologies, there are likely to be significant challenges in automating output vetting through differential privacy within a secure environment. The manuscript should address these challenges if they exist. Additionally, requiring users to conduct their analyses in OpenDP may introduce a steep learning curve.

Response: I have added a brief discussion of how this might work if disclosure-avoidance could be incorporated into such a system. At a simple level, the impact of disclosure avoidance should be assessed ex-ante

In a similar vein, instead of choosing between validation servers and containers, there could be potential in integrating these technologies. For instance, validation servers could be containerized and distributed across institutions, allowing researchers to submit queries locally. These queries could then be routed to a centralized secure environment, such as one maintained by the Census Bureau, ensuring controlled and consistent query processing across institutions. Including a discussion of these ideas in the document's discussion section would provide valuable insight into how containers and validation servers could work together to advance secure, scalable access to confidential data, and automatic output vetting.

Response: The suggestion is intriguing, but highlights issues of trust and certification between institutions - not insurmountable, but also probably not lightweight (as we have investigated in a separate project https://transparency-certified.github.io/ that has not yet written up the ideas).
For now, I have simply added universities in the discussion:

> Providing evidence of successful reproducibility (validation) may require the use of third parties, such as aforementioned commercial providers, but also universities or other research institutions.

There are several minor comments that need to be addressed in the manuscript:

- *Ensure all typos are corrected (like Howver) and that all acronyms and initialisms are clearly defined upon first use (like SSB, FSRDC).*
- *There is no reference to Figure 1 in the main text. If possible, the provided diagram in Figure 1 could include information on where containers are used or rebuilt to clarify the workflow.*
- *On page 11, the purpose of the sentence, "which runs for about 3 minutes on a 2021-vintage Linux workstation," is unclear. Consider clarifying its relevance to the reader.*
- *On page 9, the phrase "(need cite)" appears and should be replaced with an appropriate reference.*
- *In section 6.3.4, the sentence, "Should the data custodian have doubts about the verified run of the capsule," requires further clarification on why the data custodian might have doubts about the capsule's verified run.*

Response: I believe I have addressed all of these.

Reviewer 2:

Solutions to issues in both researcher access to confidential data and reproducibility of results are important, and this paper addresses these issues in novel ways and demonstrates very compelling applications at a federal agency. Even reading the paper carefully it was difficult to discern the main conclusion and contribution from the various discussions though. Renaming the manuscript to relate to Census data, or the facilitation of research on synthetic data, might help the reader since the current title implies a new innovation in HIPAA compliant containers. Nonetheless there should be a discussion about the relationship of this contribution to the costs of requirements to obtain HIPAA compliant containers vs relying on synthetic datasets.

Response: I appreciate the viewpoint, as I had been blissfully ignorant of HIPAA compliant containers - these are simply not present in any of the discussions in the social science data confidentiality setup that I have been involved in. In economics as much as in sociology and political science, most academics do not even know what containers are, and certainly don't interact with HIPAA in almost any circumstance.
I have reviewed what one can learn about HIPAA compliant containers, the context in which they are deployed, and identify where there is a connection. As the reviewer managed to glean from my previous version, the context here is not in securing containers, but in using unsecured containers - those that do not need to be secured - to improve access. I reference a few situations - not just HIPAA - where containers are used in secured environments. Most of those that I am aware of are deployed within an entire environment that is secure by whatever rule (not HIPAA, but GDPR or US Government security), and so the internal structure is less important. I hope this properly delineates the current approach from others where containers themselves play a more dominant role.

After I realized the manuscript was not on technical developments for containers, I got the impression it was a discussion of human interaction with a pilot design for an experiment at the Census bureau, but the manuscript does not take this further. In short the manuscript needs rewriting for improved clarity at the outset, including clearing stating the purpose of the work, what the work was, and the findings.

Response: I hope that the present rewrite clarifies this, with changes throughout the text.

There is related work in applications of the "Common Task Framework" (see Donoho 2024 https://doi.org/10.1162/99608f92.b91339ef) and using a container as a reproducible pipeline for checking against withheld test data by a federal agency (e.g. NIST) should be compared to the approach presented here.

Response: I now relate to the Common Task Framework, but delineate from the challenge paradigm that Donoho (2024) and others reference. In Donoho's classification, this is meant (possibly) for exploratory analysis.

The authors also appear to be presenting new standards for reproducible research code publication (e.g. section 6.1) yet don't reference the extensive body of literature on this topic.

Response: This was absolutely not meant as a new standard for research code publication. There are too many standards already (none of which is followed in the social science literature that I am familiar with). This is meant purely as a requirement of the validation. I have clarified that.

Ideally a link to their census example can be included in the manuscript, allowing readers to try out the example.

Response: I have added a link to the Github repository for the example.

The ideas in the manuscript will generate lots of reader interest if they can be presented more clearly.

Response: Thank you for your feedback!

Referee 3

A definition of containers should be included in the abstract.

Response: I have added a brief definition of containers in the abstract.

It should also be included early in the main body of the text.

Response: Excellent point, and I have added it there.

At the very least, the author should consider including a short roadmap paragraph at the beginning of the paper so that readers know what to expect. Right now, as is written, containers do not appear until Section 5, leaving readers wonder what the paper is really about before reaching that point.

Response: You are absolutely right, and this has been (hopefully) corrected.

2. The Media Summary seems missing.

Response: I have added a media summary.

3. Section 2 paragraph 1: SSB is not defined nearby, but rather in Section 6.

Response: Apologies for that oversight.

4. Table 1: It is unclear what each column is about until reading relevant text. It would be helpful to add some information about the confidence interval overlap, such as "the closer it is to 1 the higher the utility" in the table caption.

Response: Apologies for that oversight.

5. Figure 1: It is not mentioned in text what Figure 1 is for and about.

Response: The figure was aspirational. I have simplified the figure, and juxtaposed it to the proposed workflow, which hopefully provides additional clarity.

6. Page 5 middle paragraph: The second sentence starts with talking about Statistic Canada and microdata.no but ends with the 2018 paper.

Response: I'm not sure what this comment refers to. All four examples refer to examples of scaling up access to restricted-access data, and are discussed (very briefly) in the next sentence. ("scale up access to confidential data. To cite a few examples,..." No change was made.

7. Page 5 last paragraph: The author talks about "social sciences" generically but the reference is on economics. Some edits should be added.

Response: Thank you for pointing that out. The reference is to economics replication packages, since that provides a measurable statistic. I am not aware of a similar collection effort for sociology or psychology, possibly in part because it is harder to parse each article's reproducible materials at scale. I have added this explanation in a footnote,

> Footnote: Code run in November 2023, searching for any filename that contained the strings 'main' or 'master', the most common name used for control code in economics. I am not aware of a similarly comprehensive collection for other social sciences.
>
> Text: This is also my impression from our own efforts at the LDI Replication Lab supporting the AEA Data and Code Availability Policy, though we no longer make a systematic effort to categorize this.

and expanded the reference to point to the various metastudies documenting reproducibility challenges in sociology, economics, political science, and psychology.

> Footnote: I define "interactive computing" as any sequence of computational codes that must be explicitly — through edits — adapted to the environment it is running in, and/or does not have a streamlined workflow that can be triggered from a single file, regardless of workflow technology. Examples of workflow management "systems" range from `make` (1976) (Association for Computing Machinery, 2003) to `Snakemake` (Mölder et al., 2021), to literate programming tools such as `Sweave` (Leisch, 2002) and Quarto (Allaire et al., 2024), to simple concatenated calls to software (canonical `run.sh`).
>
> Text: Examples abound, and can often be gleaned from the fact that many of the reproducibility meta-studies only succeed in reproducing a small number of studies due to limitations in personnel time.
>
> Footnote: Stockemer et al. (2018) note "lack of organization in code and data presentation was the main reason that we were unable to replicate some results" in political science articles. Stodden et al. (2018) notes that only 32% of packages in Science required only minor or no effort to reproduce, though some of the reasons listed are unavoidable (GPU setup, custom hardware) and not related to workflow issues. For the economics journal studied in Herbert et al. (2024), only 24% required no change to the code in order to be able to run, even when the ultimate results was full reproducibility.

8. Section 6.2: The first sentence seems incomplete.

Response: I'm not sure I follow, though I think the sentence is maybe too long. The sentence in the submitted version, this sentence read

> 6.2. **Validating reproducibility**. In its base configuration, Codeocean signals to researchers the successful completion of a run of the controller script 'run' in the right pane of the user interface, indicating to the custodian of the confidential data that the code is verified to execute on the synthetic data.

I have rewritten this to be grammatically somewhat less complex, but also maybe clearer in what I wanted to convey.

> The Codeocean interface signals to researchers the successful completion of the controller script (called `run`) in the right pane of the user interface. To the custodian of the confidential data, this indicates that the code is verified to execute without error on the synthetic data. The results produced by this specific run of the controller script, and not any previous interactive run, are the results provided in the "results" pane. This is important for scalability and efficiency, as it reduces the need for extensive debugging, on the researcher side, and allows for rapid assessment of basic reproducibility by the data custodian.

9. Any comments/references/examples with Python?

Response: The example is provided as Stata, because most of the users in economics (the original addressees) are Stata users. However, I now point out that this is purely for illustrative purposes. If desired by the reviewer and editor, an equivalent R example could be constructed as a supplement to the existing Stata-based Github example (independent of the description in the text). A python example would not be useful for social scientists, given the low user base there.