**New Approaches to Characterize Industries: AI as a Framework and a Use Case**

**Perspective from Federal Statistical Agencies**

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## 1. AI Measurement: The Current State of Play

The current federal statistical approach to measuring industries, products, jobs and other aspects of the U.S. economy is evolutionary rather than revolutionary. For several reasons, measurement methodology and classification changes often take several years to become part of official statistics. Yet there is significant pressure to innovate how federal statistics are produced and disseminated to assure the agencies meet their mandate to produce relevant, timely, accurate, and objective data. The American Statistical Association and George Mason University have undertaken a research project to measure annually the health of the Federal Statistical System (FSS)[2]. Timeliness and relevance of data releases and the ability to innovate are among the key metrics.[3]

Innovation in federal statistics requires investment of agency resources, skilled staff, and sustained high-level attention from leadership. The ability to bring these characteristics together differs significantly by agency. The Census Bureau has roughly 7,500 permanent employees (of whom about 2,320 are statisticians and economists) and an annual budget of $1.5 billion. At the other end of the spectrum is the Bureau of Justice Statistics, with 52 employees (of whom about 33 are statisticians) and an annual budget of $42 million (OMB, 2024). Each of the FSS agencies have varying degrees of control over their resource levels, hiring, and autonomy to set priorities, define their data products, and develop statistical methodology.

In addition, the FSS is often overlooked by government policymakers when activities involve open data and AI. For example, Executive Order 13859: Maintaining American Leadership in Artificial Intelligence (2019) required federal agencies to take major steps in supporting AI R&D, prioritize efforts to grow an AI ready workforce, and make federal data assets available to

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[2] The Federal Statistical System is composed of 13 designated statistical agencies and also includes roughly 100 units scattered throughout agencies that conduct statistical activities but are not formally recognized. The 13 agencies are U.S. Census Bureau (DOC), Bureau of Economic Analysis (DOC), Bureau of Labor Statistics(DOL), Bureau of Justice Statistics (DOJ), Bureau of Transportation Statistics (DOT),Energy Information Agency(DOE), Economic Research Service (USDA), National Center for Science and Engineering Statistics (NSF), National Center for Health Statistics (CDC), National Center for Education Statistics (DoEd), , National Agricultural Statistics Service (USDA), Office of Research and Evaluation (SSA), and Statistics of Income (IRS).

[3] Assessing the Health of the Principal Federal Statistical Agencies
https://www.amstat.org/policy-and-advocacy/assessing-the-health-of-the-principal-federal-statistical-agencies

the public to advance development of AI in the U.S. Missing from the EO was any mention of funding the development of methods to measure the outcomes of these new or stepped up efforts. This omission was particularly noticeable because the President had signed the Foundations of Evidence-Based Policy Making Act just one month prior to the release of the EO, in January 2019. The Evidence Act requires agencies to establish learning agendas and build capacity for evaluating programs. However, as of 2023, no funding had been made available to the FSS agencies specifically to establish standard methods for measuring the effects of AI on the labor force and economy. Subsequent AI-related Executive Orders also do not include statistical measurement provisions (EO, 2020) (EO, 2023).

Thus, it should be no surprise that the development of statistical measures to assess the effects of AI on the economy are nascent. The largest of the 13 agencies, the U.S. Census Bureau, which has a relatively robust R&D budget, has taken steps to measure automation, technology and the associated workforce, teaming up with the National Center for Science and Engineering Statistics (NCSES) to add questions on AI beginning with the 2019 Annual Business Survey.[4] The Annual Business Survey collects information from over 300,000 firms on the use of five technologies: AI, robotics, dedicated equipment, specialized software, and cloud computing. According to 2019 survey data, adoption is concentrated on large and young firms (Acemoglu, Anderson, Beede, Buffington, & et. al., 2022). Another survey conducted as a joint project between the Census Bureau and NCSES is the Business Enterprise Research and Development (BERD) Survey[5], which is the primary source of information on research and development (R&D) expenditures and R&D employees of for-profit, publicly or privately held, nonfarm businesses with 10 or more employees in the United States that performed or funded R&D either domestically or abroad.

In addition, the Census Bureau was able to transform its Business Pulse Survey, initiated as an experimental project during the COVID pandemic, into the (also experimental) Business Trends and Outlook Survey (BTOS)[6]. The BTOS has a biweekly data collection schedule, and estimates are published every other Thursday. BTOS collects information on a wide range of business conditions. Among other topics, sampled companies are asked about their current performance, as well as changes in revenue, employment, hours worked, location operating status, supply chain impacts, demand, and prices. Businesses are asked about the previous 2 weeks and for a 6-month projection. Beginning in September 2023, the BTOS sample included all employer businesses (single- and multi-location) in the U.S., excluding a few North American Industry Classification System (NAICS) codes. During August 2023, the Census Bureau initiated an AI supplement to the survey with several questions about current and future use of AI and the effect on the business's workforce during the past six months and the next six months. However, the questions on the BTOS are at a very high level, keeping the response time for businesses to

[4] https://ncses.nsf.gov/surveys/annual-business-survey/2022#survey-info
https://www.census.gov/data/tables/2023/econ/abs/2023-abs-first-look.html
[5] https://ncses.nsf.gov/surveys/business-enterprise-research-development/2021#methodology
[6] https://www.census.gov/programs-surveys/btos.html

about17 minutes. While this brevity is helpful to experiencing higher response rates, it does cut down on the level of detail provided by the survey respondents.

The Census Bureau's Center for Economic Studies (CES) has been extending its Longitudinal Business Database[7] by matching additional datasets from a variety of sources. CES is developing experimental Business Dynamics Statistics (BDS) products using newly linked data. The basic BDS data measure the net change in employment at the establishment level. The new linked data sets are intended to provide additional public use information about how firm characteristics relate to employment flows. The BDS-Innovative Firms data describe subpopulations of firms engaged in activities related to innovation. Currently available is the BDS-High Tech (BDS-HT) experimental data product[8] that merges industry-level information on STEM occupation intensity (Goldschlag & Miranda, 2016). According to the Census Bureau, the BDS-HT classifies industries as High Tech using the concentration of Science, Technology, Engineering, and Math (STEM) occupation employment as described in Goldschlag & Miranda (2020) and Hecker (2005). To create this product, the Census Bureau used 11 years of data from the 2007-2017 Economic Censuses and identified firms that had at least five times the national average STEM employment in six of the 11 years. Eleven NAICS codes were included in the industry list. Other data products are under research including experimental data products on patenting and on trademarking, using records from the US Patent and Trademark Office.

While the Census Bureau has been taking significant steps to create data products that measure the impact of technologies on business and employment, the work is very much tied to the 5-year cycles of both the Economic Census and updates of the NAICS codes. This helps the Census Bureau track changes over time and shift the 11-year window after each Economic Census.

Of course, the downsides of this gradual change are that it becomes hard to capture a rapidly changing environment in real time and the surveys rely on respondent cooperation. In the tradeoff of making more rapid changes to the survey and keeping them respondent-friendly, the data collected may not be sufficiently detailed for some analyses. However, the approach of continuing to create experimental data products makes for slow and limited progress in measuring AI. The rate at which agencies can adapt their ongoing data collections and begin new ones that focus on technological change are highly dependent on each agencies resources and staff that can be brought to bear on the effort, as well as the ability to innovate within the federal bureaucracy.

## 2. The Conceptual and Empirical Gaps and Opportunities

Some of the efforts to define AI concepts as they affect the economy and workforce, maintaining standardization across the FSS, are reminiscent of efforts to measure Intellectual Property (IP) during the early 2000s. According to Mohr and Murphy (2002) there existed a "*widespread perception that IP, rather than "brick and mortar" and other physical assets have been a major*

[7] https://www.census.gov/programs-surveys/ces/data/restricted-use-data/longitudinal-business-database.html

[8] https://www.census.gov/programs-surveys/ces/data/public-use-data/experimental-bds/bds-high-tech.html

*force in the rapid growth of GDP, productivity, and wealth that occurred during the 1990's in the U.S. Among economists, for example, the recent productivity and growth accounting literature has been intensely focused on testing the hypothesis that much of the large unexplained quotient of long-term economic growth (total factor productivity) can be accounted for by better measurement of IP and other intangible assets that are regarded as components of "knowledge capital" inputs to industry production processes*." Knowledge capital was divided into four categories by Lev (2001) and three categories by Corrado, Hulten, and Sichel (2005) capturing tangibles and intangibles. This work led to new classifications in both the NAICS and the NAPCS. An examination of this process could be helpful in devising a roadmap in the medium term for inclusion of AI in the industry, product, and occupation classification systems if warranted.

Another example of research undertaken by the FSS was the attempt to measure offshoring of manufacturing and define nonfactory goods (Kamal, 2018). The conceptual definition of "factoryless" production was summarized along three main attributes: ownership of intellectual property, ownership and control of finished products, and outsourcing transformation activities. Ownership of intellectual property was measured as research and development expenditures, number of patents, and number of trademarks. Ownership and sales of finished goods was measured as revenue. Incidence of borderless production arrangements was measured as imports, and incidence of "headquarter" activity encompassing strategic or organizational planning and decision-making activities was measured as employment in NAICS 54 and 55. Of importance was the location where activities were taking place – especially the application of IP in manufacturing overseas. Examining the lessons learned from this effort that may be applicable to defining and measuring AI could also be used in developing a roadmap and use cases.

An example that illustrates a more rapid way of moving forward with experimental data within the FSS is the Bureau of Economics satellite accounts. BEA defines satellite accounts as "supplemental accounts that expand the analytical capacity of the main system of accounts by focusing on a particular aspect of economic activity. Satellite accounts are linked to the main accounts but have greater flexibility in providing more detailed information or in using alternative definitions, concepts, and accounting conventions."[9] The digital economy research being conducted by BEA is also an important avenue to explore, giving BEA's experience and skills in developing new ways to measure the economy and workforce, as well as its access to multiple data sources.[10]

A factor that could slow down the ability to correctly define and measure AI is that many of the products being created by the Census Bureau are only accessible to a small number of researchers, similar to the problems of limited access to IRS tax data. The approach of creating linked data sets at the Census Bureau that can only be accessed through the cumbersome process of using a Federal Statistical Research Data Center (FSRDC) will benefit the small number of researchers who are adept at using FSRDCs but will not further the goals of democratizing data

[9] https://www.bea.gov/help/glossary/satellite-accounts
[10] https://www.bea.gov/data/special-topics/digital-economy

by increasing access. Measuring the effects of AI on the economy and workforce will take many people viewing this with different perspectives and questions to answer that will drive public policy. Relying on a few statistical agencies to create these new measures will not result in rapid advancement with broad acceptance of the resulting data. It will also not meet the intent of the Evidence Act.

The Evidence Act seeks to harness the potential of evidence-based policymaking by institutionalizing key principles and practices, and it includes eleven recommendations of the Commission on Evidence-Based Policymaking (Potok, 2019). The act highlights the significance of public transparency and accessibility, stressing the value of sharing evidence and data with the broader community (Potok, 2024 ). It demonstrates a commitment to enhancing data-driven governance and aligning governmental actions with empirically grounded insights. The Evidence Act mandated the formation of a two-year Advisory Committee on Data for Evidence Building (ACDEB) and charged it with giving recommendations to the Director of the U.S. Office and Management and Budget on implementation of the act, with special focus on establishment of a National Secure Data Service. This committee, comprised of experts from inside and outside government in data analysis, privacy, and governance, provided valuable guidance on how federal agencies could navigate the intricacies of data sharing and integration while upholding ethical standards and addressing privacy concerns. The advisory committee's Year 2 Report, issued in October 2022,[11] focused on expanding access to data for evidence building, facilitating data sharing, enabling data linkage, and developing privacy-preserving techniques. It also provided a vision for how the National Secure Data Service could provide coordination and capacity-building services. It aimed to facilitate the secure exchange of sensitive data among federal agencies, researchers, and policymakers.

Subtitle F Section 10375 of the CHIPS and Science Act of 2022[12]established a 5-year demonstration project for a National Secure Data Service. Congress charged NCSES with running the demonstration project to develop, refine and test models for full implementation, in accord with the recommendations of the Commission on Evidence-Based Policy and the Advisory Committee on Data for Evidence Building. NCSES has established America's Data Hub Consortium[13] and has awarded some of the $9 million a year authorized for the National Secure Data Service demonstration project to proposals that advance the knowledge that could inform future implementation. America's Data Hub potentially could be a vehicle for a record linkage project that could partner with statistical agencies, other levels of government, and academic institutions to conduct research on capturing the economic impact of AI.

Title III of the Evidence Act updated the Confidential Information Protection and Statistical Efficiency Act of 2002 (CIPSEA). Since 2002, the Census Bureau, the Bureau of Economic Analysis, and the Bureau of Labor Statistics have been authorized to make significant

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[11] Advisory Committee on Data for Evidence Building: Year 2 Report
October 14, 2022

[12] PL 117-167. 136 STAT. 1366. AUG. 9, 2022. https://www.congress.gov/117/plaws/publ167/PLAW-117publ167.pdf

[13] https://www.americasdatahub.org/

improvements in the nation's economic statistics through the sharing of tax data acquired by the Census Bureau from the IRS. However, the improvements were never realized because the corresponding changes were not made in the IRS statues to enable this sharing. Although the Evidence Act was an opportunity to change the IRS statute to enable CIPSEA to be implemented, no such changes were included, indicating again that relying solely on the FSS to take the lead in developing AI metrics and creating accessible data products to inform public policy will be a slow evolutionary process that complements but can't lead needed efforts.

The viability of state level data sharing has been successfully demonstrated by the Midwest Consortium, which has a strong governance structure and uses a secure platform to share sensitive data on education, workforce, and training, greatly increasing the value of their data to policy makers (Cunningham, Hui, Lane, & Putnam, 2022). Building multi-state capacity for data sharing is an important component to support evidence-based policymaking and can be used to start to tackle the challenge of measuring AI by making use of the collaborative data sharing partnerships that already exist and have proven to be valuable.

Another area that needs exploration is whether there is a need for Federal-wide standards on collecting information on AI. The Chief Statistician of the US in the Executive Office of the President has delegated authority from the Director of the Office of Management and Budget (OMB) to issue standards for federal agency data collection. Thus, we have standards for geography through Metropolitan and Micropolitan Statistical Areas (MSAs), race, ethnicity, and gender identification, NAICS and NAPCS codes, etc. While these standards need to be issued by OMB, it would be helpful early on to think about conducting research in a way that can feed into early standardization of terms. One of the serious barriers to combining data is lack of standardization in how terms are defined. Many of the OMB standards arose after the fact, when problems in inconsistent data collections already existed. Developing standards informed by research from early use cases could help significantly to accelerate the efforts to have standards in place to help assure high quality data products.

Finally, development of research partnerships needs to be expanded and encouraged, including academics and all levels of government.

## 3. Short, Medium, And Long-Term Next Steps (in Summary)

### Short Term

Develop two or three use cases to explore measurement of AI in the national economy and workforce. Identify vehicles for funding such research, which could make use of existing infrastructure such as UMETRICS, America's Data Hub, and other NSF and philanthropic funding mechanisms.

Engage with government policymakers to identify pressing needs for information that may help inform the selection of the most valuable use cases.

Connect with BEA on the possibility of developing satellite accounts for AI.

**Medium Term**

Engage in outreach and share results of use cases to bring in more collaborators and funding to continue the research.

Raise awareness among policymakers of the availability of data.

Explore with the Census Bureau and the Bureau of Labor Statistics on how collaborative research can inform experimental data products being developed with survey and other data.

Explore with the Chief Statistician of the U.S. the need for Federal-wide standards on AI statistical data collections and how research could be most useful in informing such standards as well as changes to the NAICS and NAPCS and occupational codes.

**Long Term**

Continue to expand research with input from the broader community.

If feasible, continue to collaborate with BEA on developing a satellite account for AI, coordinating research results.

Create a blueprint from lessons learned and best practices on the overall AI use case that can be applied to other rapid changes in the economy and society.

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