**Review** of “Making AI Count: The Next Measurement Frontier”

by D. Coyle and J.L. Poquiz.

Carol Corrado
September 29, 2025

The main theme of this thoughtful paper is that AI is reshaping production, labor markets, and household activity, but current economic measurement systems—especially national accounts—are not equipped to capture its full impact. The paper explores how to adapt our economic statistics and its frameworks to capture the AI value chain.

This review examines key challenges as seen by the authors, followed by short discussions of the need for statistics classified by business function for the analysis of AI as a GPT and the importance of recognizing data as an asset in national accounts.

## Key Measurement Challenges Posed by AI

How well will official macroeconomic aggregates, such as GDP and productivity, capture the value provided by AI? The authors' answer to this is “poorly.”

### *It takes too long*

The authors give a failing grade to the statistical system mainly because, historically, structural change in economies is reflected in national accounts with much delay. New classifications and new data gathering takes time—and this only begins after concepts are established.

“It takes too long” critique is well founded. In fact, as Coyle and Poquiz detail throughout their paper, AI is already outpacing change in statistical systems. My own work on AI and productivity growth (Bontadini, Corrado, Haskel, and Jona-Lasinio 2025) encountered this when we wished to examine total factor productivity growth in software-producing industries. One such industry is Software Publishing, where both North American and European classification guidelines call for most subscriptions sales to be recorded. But the outputs and inputs of this industry are not separately delineated in industry-level national accounts.

Software Publishing is classified in the Information Sector, a major industry sector (like Manufacturing) in the North American Industry Classification System (NAICS) introduced in 1997. The sector has undergone revisions to better classify internet-related industries, but despite these updates, software producers remain grouped with newspaper, book, and magazine publishers at the 3-digit level. While the grouping may have made sense 30 years ago, continuing to equate software with print media in the AI era is outdated and unjustified. This anomaly in our productivity statistics should have been rectified years ago.

*Is SNA 2025 any help?*

Why do I refer to "software" producers and not "AI software" producers? The 2025 SNA recommends delineation of AI software as a category of software. No sooner was the ink dry on this recommendation than the fast-paced developments in AI rendered its intention—that a separate category would enable you to "see AI" in national accounts—next to useless.

With fast and efficient LLMs, generative AI is now integrated into legacy products like Google Search and Microsoft Office and a growing market for plug-ins and extensions has been created. How should this array of software tools be categorized? In cases where legacy functions dominate, arguably Microsoft Office, new AI features (like Copilot, itself an LLM with GPT5 capabilities), may be seen as quality improvements rather than a new software category. Meanwhile, plugins may easily qualify as distinct AI software products but whose placement in a separate category as tenuous as the probability that Microsoft or another established company will acquire them.

The bundling of AI capabilities with legacy software tools may be an opportunity for price researchers to develop hedonic price indexes for software, however. A structure of differentiated products is typical in dynamic markets, for which operational hedonic approaches to price estimation have been developed (Pakes 2003) and that, with some delay (that word again!), are now in use at the BLS (Brown and Smucker 2024).

Stepping back, the basic point here is that, to the extent that AI has *already* found uses in bundled or standalone software products, our system is not distinguishing AI's penetration, much less its functionality in quality-adjusted terms. This goes back to the crucial point in Coyle and Poquiz, that we need to work *now* to capture the transformative impacts of AI. How might we proceed?

*Software production and use as a place to start*

Coyle and Poquiz do not discuss software per se or but rather discuss "AI services" as an intermediate input that presently is not counted. The previous discussion implied that AI capabilities are in fact contained in existing measures of newly produced software; moreover, *expectations of future AI capabilities are reflected in the present-day conduct of software R&D*. The impact of AI on economic activity can then be inferred from investment and productivity data on the production and use of these software capital assets.

Economists have learned much about the aggregate economic impact of technologies such as steam, electricity, and IT with a “production and use” accounting approach. Is this time so different that the same conceptual approach cannot be used to estimate the impacts of AI technologies? In fact, this is the approach taken in Bontadini et al 2025, and its findings suggest that there has already been a *very large* impact of AI on economic growth in the United States—the production and use of software and software R&D assets in existing data accounts for about ½ of the growth in US nonfarm labor productivity from 2017 to 2024.

*Granularity in data and mechanisms of change*

Here is where the Coyle and Poquiz paper shines. They list six key challenges to counting transformative AI on the “value” side. The first three are: (1) Measuring the unpriced economic value from AI; (2) Identifying AI services in surveys of inputs to production in detailed surveys and using this information to update input-output accounts; and (3) Accounting for “improved outcomes” due to the use of AI across a broad range of industries. They also have a very informed, in-depth discussion of statistical needs on the labor market and household activity sides, producing recommendations to collect data on worker tasks (jobs remain but tasks change) and to further develop measures of consumer welfare.

One of the key takeaways of the paper is its argument for time as a measurement dimension. As the automation capabilities of AI reshape production processes, the allocation of time across work, leisure and consumption is likely to shift. The “Time” section of the paper is a must read, as is the chapter-length discussion in Coyle (2025).

The authors emphasize the importance of having proper “outcome” measures, which in many cases involves the use of quality-adjusted input and output prices of AI-using industries. I am less convinced of the urgency Coyle and Poquiz place on updating input-output information and believe the same urgency should be given to updating capital flow tables where information on software asset use is found in national accounts. That said, their basic point remains relevant: as AI software finds new uses and diffuses across industries in different proportions than legacy software has, these underlying tables will need to be updated with new statistical information.

All told, Coyle and Poquiz wish for very granular, official statistical information so that we can “see” the association between cost reduction and AI use. They suggest that TFP, for example, is not useful because it does not reveal the “specific mechanisms” through which AI improves productive efficiency. This is an understandable from a certain perspective but note: TFP *will* capture the AI-induced cost reductions in industries, just as it has for previous new technologies (and the many firm-level/microdata studies of IT use have demonstrated). Further, an abiding policy concern is whether technology adoption engenders social returns (technology spillovers), for which actual, calculated TFP provides a baseline for subsequent analysis.

Business leaders and policymakers have a deep interest in the cause/effect mechanisms that follow technology adoptions, in line with the priorities of Coyle and Poquiz. Of equal importance to stakeholders is the ability to frame the relative importance of advances in technology in aggregate terms, which requires up-to-date GDP and TFP statistics.

**Business functions and organization change**

Business functions are activities that enterprises must carry out regularly, either internally or externally, to bring goods or services to the market. Business functions are the "occupations of enterprises" and, though they can be associated with specific industries, worker tasks, or products in a general way, business functions *are not reducible* to other classifications. Examples of business functions are management, research and development, information technology, marketing and sales, and transport.

Analysis of statistics by business function reveals the presence of systemic change in the organization of production and employment by firms in economies, statistics that clearly seem relevant for understanding *within-firm* organizational change due to transformative AI. For example, a 2024 McKinsey survey found 78 percent of organizations use AI in at least one business function, most often in functions such as marketing, customer relations, and product design; least often in strategy and pricing.[1]

As AI capabilities continue to evolve and become increasingly transformative, the application areas of AI will inevitably shift. However, without an established statistical framework to analyze trends in the functional application of AI agents in production, identifying systemic change in the shape and scope of organizations will remain challenging.

**Data as an Asset**

The 2025 SNA recommends the recognition of data as an asset, a move spurred the business world's hype over Bigdata and predictive machine learning, i.e., before the generative AI era with LLM's trained on opensource datasets. That said, the SNA's recommendation that data be capitalized remains very relevant for counting the (rivalrous) proprietary data used within firms. The move improves the coverage of intangible assets in

---

[1] https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai#/ Accessed September 27, 2025.

national accounts though the extent of the improvement will depend on how the recommendation is implemented; see the discussion in Corrado et al. (2025) for a cautionary take.

The SNA recommends a cost-based method for valuing data assets, which Coyle and Poquiz believe is problematic due to nonconstant returns to the data used in AI model training. This point is not very relevant for national accounts capital measures once one considers that data assets have multiple uses and that aggregation over age cohorts, i.e., blending assets of different vintages at different stages of their efficiency cycle, leads to a smoother and more stable efficiency profile than that of individual assets.

**Conclusion**

Coyle and Poquiz are advocates for quality-adjusted price statistics, more granularity in data collection to trace the impacts of AI, and new frameworks for economic statistics (time), to which I would add activity by business function for the analysis of systemic organization change.  They also call for global coordination, new satellite accounts, and the integration of novel data sources into official statistics. The paper presents sound reasoning for the urgency of moving on multiple fronts given the pace of advancements in AI.

The authors do not prioritize strengthening the data in growth accounting frameworks that traditionally are used to assess the economic impacts of technologies (steam, electricity, IT). They emphasize that updating national accounts during periods of change is a lengthy process. But the national accounting framework remains conceptually important, and its data—valued for coverage and time-series consistency—continue to be widely used by policymakers, who also recognize its limitations. Taking this perspective, this review aimed to supplement the paper and mentioned steps to further support this approach.

**References**

Coyle, Diane. 2024. *The Measure of Progress: Measuring what Matters.* Princeton University Press.

Craig Brown, and Jeremy Smucker. 2024. “Alternative Data Sources for High-tech Products in the CPI.” *Monthly Labor Review* (December). https://doi.org/10.21916/mlr.2024.23

Corrado, Carol, Jonathan Haskel, Massimiliano Iommi, Cecilia Jona-Lasinio, Filippo Bontadini. 2025. “Data, Intangible Capital, and Productivity.” In *Technology, Productivity, and Economic Growth*, edited by John Haltiwanger, Erich Strassner, Susanto Basu, and Lucy Eldridge. University of Chicago Press.

Bontadini, F., C. Corrado, J. Haskel, and C. Jona-Lasinio. 2025, "AI as an Innovation in the Method of Innovation: Implications for Productivity Growth in the United States and Europe." (mimeo, September 19).

Pakes, Ariel. 2003. "A Reconsideration of Hedonic Price Indexes with an Application to PC's." *American Economic Review* 93 (5): 1578-1596.