White Paper: Workshop on New Approaches to Characterize Industries

Measuring AI

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Introduction

The purpose of economic measurement is to guide decision-makers, government and private sector alike. Yet even after some decades of technological transformation the structure and trends in consumption and production in modern economies are all but invisible in the available statistics. About four fifths of the advanced economies can now be characterized as 'hard to measure' (Griliches 1994, Coyle 2024 forthcoming). This indicates the need for a different approach, a need made even more acute by the rapid development and deployment of AI currently, and potentially others (innovations such as quantum and biomedical technologies, or processes such as additive or bio-manufacturing) in the short to medium term.

The challenges for statisticians are two-fold. One type is data collection. Existing classifications of sectors or occupations map poorly onto current production and consumption patterns, and there is resistance to updating classifications in ways that are not backward-compatible or suitable for low- and middle-income economies. Many researchers have begun to use a range of innovative data collection techniques, in arrangements with private data companies, or methods such as web-scraping or processing open satellite data (e.g. Donaldson & Storeygard 2016, Einav & Levin 2014). Statistical agencies are endeavouring to agree better data access with the tech companies, with limited success. For example, there is no official index of the price of cloud computing services because the companies do not provide data, so the available indices are constructed from web-scraped prices (Byrne et al 2024, Coyle & Nguyen 2019, Coyle & Hampton 2024). The use of cloud services, not capitalized in company accounts, has shifted business expenditure from capital investment to intermediate consumption, but the scale is unknown. Recent research taking an engineering-based approach to the cost of computation – using two different methods to incorporate developments in AI – shows that the pace of decline has been substantially greater than any official price index (Byrne et al 2023, Coyle & Hampton 2023). In any case, official statistics in these technology domains are generally not timely enough for decision purposes. New measurement systems are essential to fill the empirical gaps.

This White Paper is concerned, though, with the second type of challenge, which is conceptual. It suggests a framework for measuring the economic value of new technologies such as AI, given that general purpose technologies cause structural shifts in the economy. It also highlights some key economic research questions.

The economic value of AI

At the heart of understanding economic progress is the process of turning resources into valued goods and services. One analytical building block is the production function. The KLEMS approach (Jorgenson and Griliches (1967), Jorgenson et al (1987), Schreyer & Pilat (2001)) has become a standard growth accounting tool representing this. It is incomplete: first, because it provides a year-by-year snapshot that does not capture the dynamic process especially as it requires the assumption of constant returns to scale, whereas process innovations are important sources of productivity growth, involving inherently increasing returns (Table 1); secondly, because it omits structural change in consumption.

Table 1: Examples of productivity growth from process innovation

Process	Date	Key technology
American system of manufactures	early C19	machine tools
Factory system	mid-late C19	steam, rail
Assembly line	early C20	electricity
Lean manufacturing	late C20	telecoms, early digital
Production networks	late C20- C21	ICTs
Digital platforms (production & consumption)	early C21	ICTs, AI
Novel manufacturing processes	mid C21	AI, additive, bio

Author's own, from Coyle 2025 forthcoming.

Nevertheless, KLEMS offers a useful starting point. The variables will be indexed by sector/firm and by time period t. Rates of growth in aggregate inputs and gross output are weighted averages of their individual components, with the weights given by relative shares of each component in the total. If we assume technology is Hicks-neutral (that is, increasing the marginal productivity of all inputs equally), then differentiating the production function with respect to time and using log rates of change gives the familiar decomposition equation:

$$d \ln A/dt = d \ln Y/dt - s_K \, d \ln K/dt - s_{AI} \, d \ln K_{AI}/dt - s_L \, d \ln L/dt - s_M \, d \ln M/dt$$

(Note, if value added measures are used rather than gross output, the weights s are the factor shares in value added; but this will overstate the rate of TFP growth by a factor of the inverse of the share of value added in gross output; as this has been declining, the degree of over-statement will have increased over time.)

Here AI capital has been distinguished from other capital. Existing produced capital measures in principle account for the physical infrastructure of AI, such as servers, chips and data centers, although there is a need for more focus on collection and development of these capital stock and services data; here the separate category highlights the distinctive new intangible capitals: models and data. There is a growing research literature and statistical effort on measurement of intangible capitals, of which this is a natural extension (Corrado et al 2022). Measurement of the models' intangible capital services is a new area, requiring joint work with AI experts, but there is considerable collection under way of useful benchmarks (re Stanford overview). There is a little more progress on the measurement of the value of data (see Coyle & Manley 2023 for a recent survey). Again, this is ripe for further development. In work in progress, Coyle & Gamberi (in progress) are piloting an approach taking advantage of the Shannon entropy measure when noise is added to a dataset.

However, this gives us a first snapshot. The next step is to consider the information enabled by using AI as an input to a knowledge production function, in an endogenous growth framework. A standard formulation is:

$$\Delta A_t/A_t = \theta . H_{At.} A_t$$

where H is the stock of human capital and $\theta>0$ is generally interpreted as a research productivity parameter. Empirical applications have focused on codified knowledge, or conventionally measured skills, but tacit know-how and socially-embedded capabilities ('organisational capital') would equally drive knowledge production and growth, either through H or the parameter θ. In the context of AI and other new technologies, Lane (2023) has underlined the need to measure exactly these aspects and provided a framework for statistical implementation. A related question not addressed by labour market and skills data is the organisational capital of firms: what is it that distinguishes AI users from non-AI users. A number of researchers (e.g. Gal et al 2019, Cathles 2020, Brynjolfsson 2021, Coyle et al 2022) have linked growing productivity dispersion at firm level to differential use of digital tools of various kinds, so there is an open question about the barriers to adoption. This is an open part of the research agenda, where data collection depends on better understanding the organisational or tacit knowledge barriers to AI use (Bessen 2022).

The final step in this economic value framework poses the biggest conceptual challenge, and I believe this is a wide-open research question. It concerns the link from production to consumption and how to value the use of AI in the economy at the level of final demand. The issue is how the revenues counted inside the production boundary are to be converted into estimates of the 'real' economy, or in other words the deflators. There is a massive literature on the well-known challenges of constructing price indices, particularly when there are large changes in patterns of output and consumption, or increased variety and many new goods and services, as now (Diewert et al 2009, Coyle 2024a forthcoming). Similarly, issues arising from the (incorrect) assumption of homothetic demand to construct the indices generally used by statistical agencies are well known (Stapleford 2009).

The new challenge stems from changes in consumption technologies. Abdirahman et al (2022) noted that the constructed price index for telecommunications services in the UK varied enormously depending on whether revenue or volume weights are selected for combining specific service prices into the sectoral index. Telecoms companies charge a higher price per byte of data for traditional services such as fixed line calls and SMS. The explosion of data use means that a volume-weighted sector price index plunges, while a revenue-weighted index declines more modestly. Which is correct? Neither. We would not want to attribute real economic value to the fact that operators price differentiate among similar services (eg. SMS versus WhatsApp), which is the case with revenue weights. Nor would we want to attribute equal value to every byte because what consumers care about is the content of the bytes. The conceptual challenge is that the product demanded is a bundle of telecoms services, data center services, device services and (sometimes free) content services. While some work (see Byrne & Corrado 2019 on consumer device services and e.g. Brynjolfsson et al 2019, Coyle & Nguyen 2023 on free online services) has looked at the separate elements, there remains an open question about how to conceptualize and categorize the relevant economic activities. One promising suggestion (Hulten & Nakamura 2020) is to use Lancaster's (1966) framework to conceptualize a 'consumption technology' shift. In any case a starting point is to identify the underlying data needs to explore the relevant 'services' consumers value.

Summary

This White Paper has proposed using standard economic models to establish an input to output measurement framework for AI. It would be applicable with modification to other general purpose technologies. Table 2 summarizes the stages and data needs.

Table 2 Summary of framework and data needs

Production	KLEMS	Intangible AI capital (value of models, data); enhance collection of physical AI capital data (eg data centers, fibre networks). Price indices.
Knowledge production	Endogenous growth process	Research & skills, employment & wages in AI; organisational capabilities (eg by management survey).
Demand & Consumption	Consumption technology	Consumer device purchase, data usage by category. Price indices.

However, there remain some open deep economic questions in order to understand why and how new general purpose technologies mean the major part of the advanced economies is 'hard to measure'.

References

Abdirahman, M., Coyle, D., Heys, R. & Stewart, W. (2022). Telecoms Deflators: A Story of Volume and Revenue Weights. *Economie et Statistique /Economics and Statistics*, 530-31, 43–59. doi: 10.24187/ecostat.2022.530.2063

Bessen, J. (2022). *The new goliaths: How corporations use software to dominate industries, kill innovation, and undermine regulation*. Yale University Press.

Brynjolfsson, A. Collis, W. E. Diewert, F. Eggers, and K. J. Fox. 2019. GDP-B: Accounting for the value of new and free goods in the digital economy. Working Paper 25695, National Bureau of Economic Research

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1), 333–372. https://doi.org/10.1257/mac.20180386

Byrne, D., Corrado, C., & Sichel, D. E. (2018). The rise of cloud computing: Minding your P's, Q's and K's (NBER Working Paper No. 25188). National Bureau of Economic Research.

Byrne, D., & Corrado, C. (2019). Accounting for Innovations in Consumer Digital Services: IT still matters (Finance and Economics Discussion Series No. 2019-049). Board of Governors of the Federal Reserve System. https://doi.org/10.17016/FEDS.2019.049

Byrne, D. M., Hamins-Puertolas, A., & Harnish, M. M. (2023). Transistors all the Way Down: Viability of Direct Volume Measurement (and Price Indexes) for Semiconductors. Working paper.

Cathles A, Nayyar G, Rückert D. (2020). Digital technologies and firm performance: Evidence from Europe. European Investment Bank (EIB). (EIB Working Papers).

Corrado, Carol, Jonathan Haskel, Cecilia Jona-Lasinio, and Massimiliano Iommi. (2022). "Intangible Capital and Modern Economies." *Journal of Economic Perspectives,* 36 (3): 3-28.

Coyle, D., & Manley, A. (2023). What is the value of data? A review of empirical methods. *Journal of Economic Surveys*, 00, 1–21. https://doi.org/10.1111/joes.12585

Coyle, Diane, and David Nguyen (2019). Cloud Computing, Cross-Border Data Flows and New Challenges for Measurement in Economics, National Institute Economic Review, https://doi.org/10.1177/002795011924900112

Coyle, D. & Nguyen, D. (2023). Free Digital Products and Aggregate Economic Measurement. *Economie et Statistique / Economics and Statistics*, 539, 27–50. doi: 10.24187/ecostat.2023.539.2096 https://www.insee.fr/en/statistiques/7647309?sommaire=7647685

Coyle D, K Lind, D Nguyen, M Tong (2022). Are Digital Using UK Firms More Productive ESCoE Discussion Paper 2022-06 https://www.escoe.ac.uk/publications/are-digital-using-uk-firms-more-productive/

Diane Coyle, Lucy Hampton, (2023). 21st century progress in computing, *Telecommunications Policy*, https://doi.org/10.1016/j.telpol.2023.102649.

Coyle, D. (forthcoming 2024). Productivity Measurement: New goods, Variety and Quality, in *Productivity Measurement* eds Karen Dynan & Marshall Reinsdorf, Brookings Institute/U of Chicago Press,

Coyle, D (2024a forthcoming). Old Wine in New Digital Bottles, *Review of Income and Wealth*.

Coyle , D. (2025 forthcoming). *Measuring Economic Progress.* Princeton University Press.

Coyle D & L Gamberi (in progress).

Donaldson, Dave, and Adam Storeygard. (2016). "The View from Above: Applications of Satellite Data in Economics." *Journal of Economic Perspectives,* 30 (4): 171-98. DOI: 10.1257/jep.30.4.171

Diewert. W.E., J.S. Greenlees, C.H. Hulten, eds (2009). *Price Index Concepts and Measurements*, NBER/University of Chicago Press.

Liran Einav and Jonathan Levin , (2014). Economics in the age of big data. *Science.* DOI: 10.1126/science.1243089

Gal, P., et al. (2019), "Digitalisation and productivity: In search of the holy grail – Firm-level empirical evidence from EU countries", *OECD Economics Department Working Papers*, No. 1533, OECD Publishing, Paris, https://doi.org/10.1787/5080f4b6-en.

Griliches, Z. (1994). Productivity, R&D, and the Data Constraint. *The American Economic Review*, *84*(1), 1–23.

Hulten, C., & Nakamura, L. (2020). Expanded GDP for Welfare Measurement in the 21st Century. In C. Corrado, J. Miranda, J. Haskel, & D. Sichel (Eds.), *Measuring and Accounting for Innovation in the 21st Century, NBER Studies in Income and Wealth*. Chicago: University of Chicago Press.

Jorgenson, D. W., Gollop, F. M., & Fraumeni, B. M. (1987). Productivity and U.S. economic growth. North-Holland.

Jorgenson, D. W., & Griliches, Z. (1967). The Explanation of Productivity Change. The Review of Economic Studies, 34(3), 249–283. https://doi.org/10.2307/2296675

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132–157

Lane, J. (2023). The Industry of Ideas: Measuring How Artificial Intelligence Changes Labor Markets. https://www.aei.org/research-products/report/the-industry-of-ideas-measuring-how-artificial-intelligence-changes-labor-markets/

Schreyer, P., Pilat, D. (2001). Measuring productivity. OECD Economic Studies 33 (2), 127–170.

Stapleford, Thomas (2009). *The Cost of Living in America. A Political History of Economic Statistics 1880-2000*. Cambridge University Press.