NBER/Conference on Research in Income and Wealth, *Technology, Productivity and Economic Growth*

Introduction

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Today's economy is experiencing an explosion of technological advances that are far beyond what was imaginable even five years ago. This fast pace of innovation is pervasive across industries and countries. This volume considers if there are new and better ways to conceptualize and model these advances and improve our measures of productivity and economic growth to capture this changing landscape. Before delving into the expert essays that comprise this book, it seems only right to define what "productivity" is. Productivity is an economic measure of efficiency that shows how effectively economic inputs are converted into goods and services. A standard measure is total factor productivity (TFP), which is output growth minus share-weighted input growth. That is, TFP measures the growth in output that is not the result of using additional inputs of labor, capital, energy, materials or services. This concept is also known as "the Solow residual" (or just "the residual"), for the famous paper in which Solow (1957) showed that under certain assumptions it measures technological change in an aggregate production function.

A year before Solow gave the residual its most popular interpretation, Abramovitz (1956) had defined it in a less hopeful manner, calling it "a measure of our ignorance." For if the residual is the share of output growth that is not explained by input growth, it must measure something that is important for economic growth but is (as yet) unexplained by economics. This challenge set a large branch of the productivity literature on a quest to transfer more and more of the sources of economic growth from the unexplained residual to inputs that were deliberately chosen by optimizing entities, either households or firms. This research program was laid out in the landmark paper of Jorgenson and Griliches (1967) and attained its modern form in the book by Jorgenson, Gollop and Fraumeni (1987).

This research program was extremely successful by its own lights. In a larger context, however, the task became a Sisyphean one. The growth accounting started by Solow (1957) and reaching its full flowering in Jorgenson, Gollop, and Fraumeni (1987) was typically set in the context of neoclassical growth, with its assumptions of perfect competition and constant returns to scale. Only in such a setting would the easily measured factor income shares correspond to the necessary output elasticities of each factor input. But in a neoclassical setting, with its assumption of diminishing marginal products to all accumulated factors of production ("capital," in a broad sense), per-capita growth in the long run could come only from exogenous technical change.

Growth accounting measures only the direct impact of technical change, holding capital fixed. But in the long run, higher exogenous productivity growth should also induce capital accumulation. In the neoclassical growth model with endogenous saving developed by Ramsey (1928), Cass (1965), and Koopmans (1966), as long as preference parameters were stable, *all* of long-run per-capita growth in output and consumption come from exogenous technical change. As growth accounting reached new heights, it transferred more of the proximate causes of growth from the "residual" to the "capital" column. But decreasing the importance of the residual by increasing capital's share in production could not illuminate the deeper sources of growth in the neoclassical framework. In the Ramsey-Cass-Koopmans framework, the reduction in the immediate impact of the residual on output growth only increased its long-run impact via induced capital accumulation, leaving the "exogenous technical change" still the sole source of per-capita growth in the long run.

The tension between "exogenous technical change" and the "measure of our ignorance" remains. That is, mismeasured or missing components of labor and capital are a continued focus of research in this area. Relatedly, it has been increasingly recognized that technical change is in fact endogenous with technological innovation arising from investments in some form of R&D broadly defined. One approach is to treat R&D capital as just another form of capital. However, such endogenous innovation may be subject to spillovers or externalities (e.g., Romer (1990) and Jones (1995)) so that such R&D or "innovation" capital is not the same as other forms of private capital accumulation. Hulten (2001, 2009) emphasized the importance of distinguishing between the "costless part of technical change" and the endogenous components that may be subject to externalities. Hulten (2009) writes, "Growth accounting formulated in this way is no longer a story about technology versus capital formation, but a story about costless advances in technology versus different types of capital formation, including those that promote technical change. Costless MFP growth arises from serendipity, inspiration, or the diffusion of technical knowledge from the originator who bears the development cost to other users." This perspective suggests that TFP is more than the measure of our ignorance, and also more than just exogenous technology that falls like "manna from heaven." Perhaps most importantly, in this new view the economy's long-run growth rate is susceptible to change through variations in institutions and economic policy.

Building on this perspective is the recognition that accounting for intangible capital in terms of both output and input measurement is important for quantifying TFP (see, Corrado, Hulten and Sichel (2005) and (2009)). This perspective is an expansion beyond the recognition that R&D capital is an important part of the dynamics of growth to include additional intangible capital investments, such as investment in business practices, databases and software. Research in the measurement of intangible capital highlights how difficult it is to measure these assets, not only in terms of nominal expenditures but in terms of depreciation rates and price deflators that capture quality adjustment. Yet, even with these challenges, quantitative analysis suggests that growth in intangible capital dominates growth in tangible capital substantially over the post 2000 period (Corrado et al. (2022)). Intangible capital investments in the increasingly globalized and networked economy also involve scale effects that provide advantages to large firms – such as for example, the investment in databases. Perhaps relatedly, the productivity slowdown in the US since the mid-2000s has been accompanied by a rapid rise in market concentration. These changes in turn raise questions about the perfect competition assumptions in output and input markets underlying standard growth accounting used to compute measures of TFP.

In March of 2022, the Conference on Research in Income and Wealth (CRIW) of the National Bureau of Economic Research (NBER) held a conference in Washington D.C. to provide a forum where economists, data providers and data analysts could present research on the state of our understanding of changing technology, productivity and economic growth. The conference invited participants to present papers from a theoretical and empirical perspective with a focus on the ongoing measurement issues and challenges on these topics. The conference drew participants from academia, government and non-academic research institutions. This volume includes the papers presented at the conference.[1]

The various views of productivity discussed above are a good way of classifying the papers that appear in this volume. Several chapters further the Jorgenson-Griliches program of

[1] The papers have undergone review and, in some cases, substantial revision since their presentation at the conference.

classifying portions of the productivity residual as input growth, either through better measurement or by expanding the range of inputs considered in productivity analysis. Other papers look for the deep sources of productivity growth that remain. Still others remind us of the "costly" portion of productivity growth, where the costs may be paid in labor disruptions or the resources consumed in producing complementary innovations.

We have grouped the papers into three broad but related categories. The first set are papers that examine issues for tracking recent changes in advanced technologies such as Artificial Intelligence and implications of these changes for productivity and for the workforce. The second set of papers focuses on puzzles and measurement issues associated with measuring productivity. The last groupings of papers focus on measuring productivity through the lens of issues associated with measuring input growth in novel and broader ways.

Changing Technology

The adoption of advanced technologies by firms often takes time and exhibits considerable heterogeneity across firms. In addition, the pace and nature of such adoption will have significant impacts on economic outcomes for both firms and workers. Given recent advances in advanced technologies, the US Census Bureau teamed with researchers to develop modules in the recently developed Annual Business Survey (ABS). The paper "**Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey**" by Daron Acemoglu, Gary W. Anderson, David N. Beede, Cathy Buffington, Eric E. Childress, Emin Dinlersoz, Lucia S. Foster, Nathan Goldschlag, John C. Haltiwanger, Zachary Kroff, Pascual Restrepo, and Nikolas Zolas explores the adoption of advanced technologies by US firms across all economic sectors by leveraging a new module introduced in the 2019 ABS. The module collects data from over 300,000 firms on the use of five advanced technologies: AI, robotics, dedicated equipment, specialized software, and cloud computing. The share of firms that have adopted one or more of these technologies is low (especially for AI). For example, as of the time of the survey in 2019, the AI adoption rate is only 3%. However, since larger firms have higher adoption rates, about 13% of workers are exposed to using AI in the workplace. Adoption rates for AI are significantly higher in sectors such as the Information sector with about 10% of firms having adopted the technology and more than 20% of workers exposed in this industry. Similar trends can be observed in the adoption of other advanced technologies. Firms report a variety of motivations for adoption, including automating tasks previously performed by labor. Consistent with this motivation, adopters have higher labor productivity and lower labor shares. Adopters report that these technologies raised skill requirements and led to greater demand for skilled labor but brought limited or ambiguous effects to their employment levels. Periodic tracking of the adoption patterns of advanced technologies and the implications for productivity and productivity by the US statistical agencies will remain vital given the continued developments of these technologies.

With the explosion of advances in AI, there is increased attention on understanding the nature and pace of adoption of general-purpose technologies (GPTs). In the paper "**Similarities and Differences in the Adoption of General Purpose Technologies,**" Ajay Agrawal, Joshua S. Gans and Avi Goldfarb provide guidance about the role of GPTs in productivity growth. Much of the literature focuses on the commonalities of GPTs as well as the required co-invention costs for productivity growth. This paper highlights that these components of GPTs are distinct and idiosyncratic. The implication is that for us to understand the impact of AI on future productivity growth we need to identify and quantify the distinct benefits and costs of the technology. The authors emphasize that AI can help predict the next word in a sequence with a host of possible applications. It can also provide predictions about likely outcomes in settings such as health care enabling guidance about tests and treatments for observed health indicators. The benefits of such predictions and the co-invention costs all depend on the specific application. The authors highlight that without identification and quantification of these distinct benefits and costs it will be difficult to understand the ongoing nature and pace of adoption of AI.

The paper "**Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition",** by Tania Babina, Anastassia Fedyk, Alex He, and James Hodson, assesses the impact of investments in artificial intelligence on the workforce. The authors take a unique approach and combine worker resume and job posting datasets to identify firm-level workforce composition and AI investments. The authors use AI themselves to develop this very impressive dataset. They find that firms with higher initial shares of highly educated workers and STEM workers invest more in AI. Moreover, as firms invest in AI, they tend to increase their shares of workers with college degrees and more specialized IT skills. Using the same data set, the authors are able to look at the firms' organizational structures and discover that firms with more AI tend to have a flatter hierarchical structure, with significant increases in the share of workers at the junior level.

Puzzles and Challenges in Measuring Productivity

Two papers in this volume explore the puzzling dynamics of productivity in the construction sector. While aggregate productivity has exhibited slower growth since the early 2000s it has still been robustly positive. Although cyclical fluctuations can yield periods of measured negative productivity growth at the aggregate and sectoral level, in the presence of technological progress, long run productivity growth is anticipated to be positive. Hence it is a puzzle, that there have been large and persistent declines in productivity for the U.S. construction sector. Moreover, because construction is a large sector in the U.S., it has acted as a drag on aggregate productivity. The paper "**The Strange and Awful Path of Productivity in the U.S. Construction Sector**" by Austan Goolsbee and Chad Syverson explores the sources of this puzzling long run decline. They find some evidence of measurement issues but their analysis suggests that this is not the whole story. Using measures of physical productivity in housing construction, they find that productivity is falling or, at best, stagnant over multiple decades. In addition, they present evidence of a decline in the efficiency with which construction firms translate materials inputs into output, and a corresponding shift toward more value-added-intensive production. They also find some evidence that reallocation activity across states has if anything been productivity detracting. At the end of the day, they don't fully identify the key factors that have led to this large and puzzling decline. Given the importance of residential and commercial construction in the economy, this paper highlights that devoting attention to this puzzle should have a high priority.

The anemic performance of productivity growth in the US construction sector is matched in many respects in the UK. For the UK, the evidence for construction is more consistent with flatlined labor productivity and mildly declining TFP. In the paper "**Digital concrete: productivity in infrastructure construction,**" Diane Coyle and Rehema Msulwa explores the impact of digitization on the structure and productivity of the UK's civil construction sector. This study is motivated by the greater use of digitization and outsourcing in this sector. The authors approach the evidence from two perspectives: the possibility that there are simply delays in the resulting productivity gains showing through; and the possibility of mismeasurement. They present evidence that both of these factors are likely to contribute. For example, in the architectural and engineering component of construction, they argue that the evidence suggests digitization has led to a greater decline in prices than in the official statistics. They also present evidence in favor of "J-curve" effects which implies that investments in new technologies take time to show up in productivity statistics. Part of the "J-curve" effect is that intangible capital investments don't get properly accounted for in output as they are difficult to measure. Another component of the "J-curve" is that there is experimentation and learning in the use of new technologies.

As we seek to better understand sources of growth in productivity, it can be useful to disentangle production between primary and secondary products within the same industry, particularly if secondary products are substantively different from primary products. When an industry includes establishments engaged in secondary production, measured TFP growth at the industry level reflects the joint production of the primary and secondary products. In addition, reallocation of resources between these products within an industry can obscure analysis of the underlying reasons for changes in aggregate TFP. In "**After Redefinition TFP Accounting**," Jon D. Samuels develops estimates of TFP growth for single product-based industries. This redefinition in TFP accounting facilitates analyzing international competitiveness where trade is driven by product competitiveness. These data are particularly useful for the analysis of global value chains (GVCs) and measuring trade in value added (TiVA). Samuels finds that distinguishing between primary and secondary production is important for measuring TFP growth, but only for a small subset of industries, including computer and electronic products and data processing, internet publishing, and other information services sectors.

Improved Measurement of Key Inputs: Capital and Labor

As artificial intelligence takes off, the need for increasingly large stores of data is growing and thus defining and measuring data has become vital to understanding growth in the economy. **"Data, Intangible Capital, and Productivity,"** by Carol Corrado, Jonathan Haskel, Massimiliano Iommi, Cecilia Jona-Lasinio, and Filippo Bontadini**,** analyzes how the increased use of data throughout the world affects productivity. The authors conceptualize data as an intangible capital asset that is a storable, nonrival factor input. Using the Corrado, Hulten, and Sichel (2005, 2009) intangible capital framework and the recently developed EUKLEMS & INTANProd database (LLEE 2023), they develop measures of industry-level investments in data assets for nine European countries. The authors find that about 50 percent of intangible capital is, in effect, data capital. Incorporating these measures of data/intangible capital in a TFP framework the authors assess the recent global slowdown in TFP. Corrado et. al argue that the increased data intensity of intangibles weakens knowledge diffusion and diminishes TFP growth. They find that the increase to labor productivity from data capital is offset by an appropriability effect, which shaved 0.3 and 0.4 percentage points off 2010-2019 TFP growth in Europe and the United States.

As economists continue to dig into the measurement of productivity, it is increasingly recognized that data is an asset that should be incorporated into capital accounts and in turn productivity. During the last revision of the System of National Accounts (SNA) (United Nations 2010 the agreement is to treat databases as a subcategory of software in capital formation. The challenge is how to measure data as an asset. The paper "**Valuing the U.S. Data Economy Using Machine Learning and Online Job Postings**" by José Bayoán Santiago Calderón and Dylan G. Rassier explores novel methods to achieve this objective. The approach taken in this paper is to measure the value of own-account data stocks and flows for the U.S. business sector by summing the production costs of data-related activities implicit in occupations. Production costs include labor costs, capital costs, and intermediate consumption. The authors apply a markup to an estimate of the wage bill for data-related activities, which is consistent with the Bureau of Economic Analysis (BEA) methodology for own-account software. The method in this paper augments the traditional sum-of-costs methodology for measuring other own-account intellectual property products (IPPs) in national economic accounts by proxying occupation-level time-use factors using a machine learning model and the text of online job advertisements. The experimental estimates indicate that annual current-dollar investment in own-account data assets for the U.S. business sector grew from $84 billion in 2002 to $186 billion in 2021, with an average annual growth rate of 4.2 percent. Cumulative current-dollar investment for the period 2002–2021 was $2.6 trillion.

An ongoing challenge for tracking productivity growth is distinguishing between lower frequency secular trends and high frequency cyclical dynamics. Complicating the latter is that measured TFP tends to be procyclical due to failure to account for variation in capital utilization. Many methods have been suggested and used to adjust for capital utilization with only limited success. This issue became especially relevant in the pandemic since output and hours declined sharply but standard measures of capital input were largely unaffected. In the paper "**An occupation and asset driven approach to capital utilization adjustment in productivity statistics,**" Josh Martin and Kyle Jones explore an extension of traditional methods which focus on variation in labor hours to capture capital utilization. The authors use hours worked for especially relevant occupations for specific assets and introduce a conceptual framework to motivate and guide this alternative approach. Applying their method to the pandemic, they find a decline in capital utilization of around 9% in the UK market sector in the height of the coronavirus pandemic, recovering over half of this by the end of 2020. This approach mitigates but does not eliminate, the fall in TFP through 2020. However, the authors find this alternative method produces less-promising results prior to 2020, particularly during the global financial crisis.

As discussed above in the context of changes in advanced technologies, such changes are accompanied by changes in the manner in which firms organize themselves and accomplish tasks. The paper "**Opening the Black Box: Task and Skill Mix and Productivity Dispersion"** by G. Jacob Blackwood, Cindy Cunningham, Matthew Dey, Lucia Foster, Cheryl Grim, John Haltiwanger, Rachel Nesbit, Sabrina Wulff Pabilonia, Jay Stewart, and Cody Tuttle explores the measurement challenges of tracking the changes in skills and tasks by firms as the economy evolves with changing technology. This paper highlights that tracking the changing task content of production at the firm level has been elusive since the firm-level data on productivity at the US Bureau of the Census does not readily include information on the skill mix or the mix of tasks. A joint project between the Bureau of Labor Statistics (BLS) and the Census Bureau is seeking to alleviate the data and knowledge gap. The objective of this collaborative project is to open the black box of tasks, skills and productivity by combining establishment-level data on occupations from the BLS with a restricted-access establishment-level productivity dataset created by the BLS-Census Bureau Collaborative Micro-productivity Project. This paper takes a first step toward this objective by exploring the conceptual, specification, and measurement issues to be confronted in this data integration. The paper also includes empirical analysis showing that within-industry productivity dispersion is strongly positively related to within-industry task/skill dispersion.

Conclusions

It is an exciting time for the field of economics that focuses on measurement of technology, productivity, and economic growth. Rapid changes in technology such as artificial intelligence appear to be on the cusp of generating rapid changes in how businesses organize themselves including their workforce and stimulating a period of accelerated growth. At the same time, there has been an explosion of big data from administrative and private data that enable tracking and studying these topics in novel ways that enable shedding light on both longstanding and new questions. New methods for using and integrating disparate data sources using techniques such as machine learning are developing in tandem with the development of new data sources. As emphasized by the papers in this volume, there are also many core open questions about technology, productivity, and economic growth that involve both conceptual and measurement issues. It is our hope that the community developing and studying the data on these topics can use the accumulated knowledge and wisdom embodied in the papers in this volume to make progress on these issues in the years to come.

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