Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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2022-038

Please cite this paper as:
Byrne, David M. (2022). "The Digital Economy and Productivity," Finance and Economics Discussion Series 2022-038. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2022.038.

The Digital Economy and Productivity

David M. Byrne*

June 6, 2022

Abstract

After reviewing the state of *digitalization*—the use of digital information technology (IT) throughout the economy—we consider the slippery concept of a distinct *digital economy* and efforts to record it in national accounts. We then anchor the digital economy in a growth accounting framework, augmenting the conventional measure of the IT contribution to productivity—innovation in the production of IT capital plus labor-saving use of IT throughout the economy—with the contribution from the digital platforms that help users navigate the sprawling information landscape. We discuss the difficult measurement issues that thwart full accounting of the scope and productivity of the digital economy. These include quantifying the intangible assets created by platforms and their users, measuring the consumption of intangible services provided by platforms—often for free—and identifying platforms within the existing statistical system, which does not treat their activity as a distinct industry.

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1 Introduction

Since the mid-20$^{\text{th}}$ century, advances in information technology (IT) have relentlessly driven down the cost of creating, storing, transforming, and transmitting information, fostering in turn the widespread use of IT and exponential growth in digitally stored information. In short, the economy has become more *digitalized*. Like electrification in the early 20$^{\text{th}}$ century, digitalization has been so pervasive that it is in the background of essentially all economic activity. Yet, the idea of a distinct *digital economy* is prevalent in policy discussions and media coverage.[1] Articles referencing the digital economy in the business press most frequently focus on the companies that mediate access to the sprawling information landscape, which we'll refer to as "digital platforms," that are central to the latest wave of the IT revolution (fig. 1 on the following page).

In this chapter, we consider three closely related but distinct questions: (1) How digitalized is the economy? (2) What are the boundaries of the digital economy (and how big is it)? (3) And, how much does the digital economy contribute to economic growth? We first describe the state of digitalization and its distinctive features in recent years, namely radical mobility, cloud computing, and digital platforms. Then, after describing emerging efforts to measure the digital economy in national accounts, we anchor the digital economy in a growth accounting framework and discuss obstacles to assessing the role of the digital economy in productivity. We argue that accounting for three distinct phenomena—the production of IT capital, its use throughout the economy, and the economic activity of digital platforms—is necessary to measure the contribution of the digital economy to productivity. Many thorny measurement problems stand in the way of that effort.

2 How digitalized is the economy?

Although digitalization—the storage, transformation, and transmission of digital data to enhance economic activity—leaves its mark on myriad in-

[1] Broader treatments of the many dimensions of this subject include Ahmad and Schreyer (2016) and Reinsdorf and Quirós Romero (2020) Though the boundaries of the digital economy aren't well defined, we seem to know it when we see it.. The particular focus of this chapter is the adequacy of digital economy measurement for growth accounting.

Figure 1: Digital Economy Companies

Note. Companies frequently mentioned in articles in the Wall Street Journal, the Financial Times, and Harvard Business Review with "digital economy" in the title. Word cloud created at http://www.wordclouds.com.

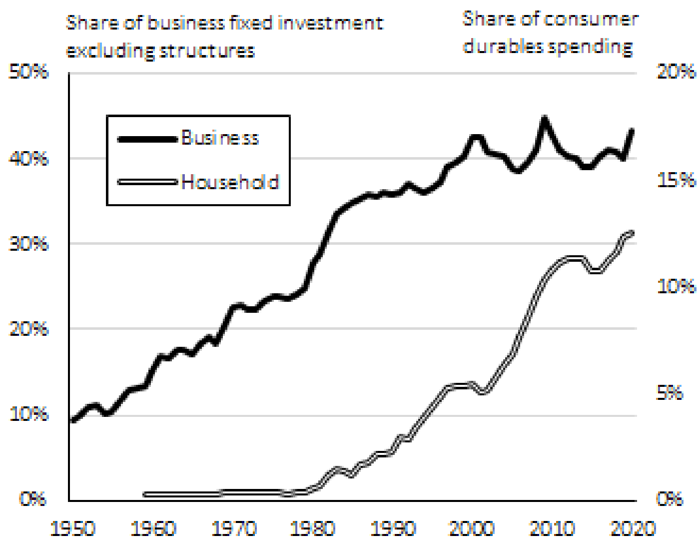
dicators throughout the economy, we focus on the use of IT capital as a barometer of the phenomenon.[2] Because digitalized activity ultimately relies on electronic equipment and software, we expect the share of IT capital in total fixed capital investment to rise with digitalization. In the United States, this was indeed the case from the dawn of electronic computing in the 1950s through roughly 2010, with the share of information technology in business investment more than doubling to over 40 percent and its share in consumer durables spending climbing from minimal in 1980 to over 10 percent in 2010 (fig. 2 on the next page).[3] More recently, the share of IT capital in business and household investment has roughly moved sideways, seeming to suggest that digitalization in the economy has stabilized.

However, beneath the surface of a fairly steady overall IT investment share in recent years, the industry composition of IT investment has changed markedly, suggesting a still-evolving digitalization process (fig. 3 on the fol-

[2]For other indicators, such as the effects of digitalization on human capital accumulation, income inequality, and R&D, see OECD (2020).

[3]In the interest of brevity, we focus on the U.S. economy. For a global perspective, see OECD (2020).

Figure 2: U.S. IT Capital Investment

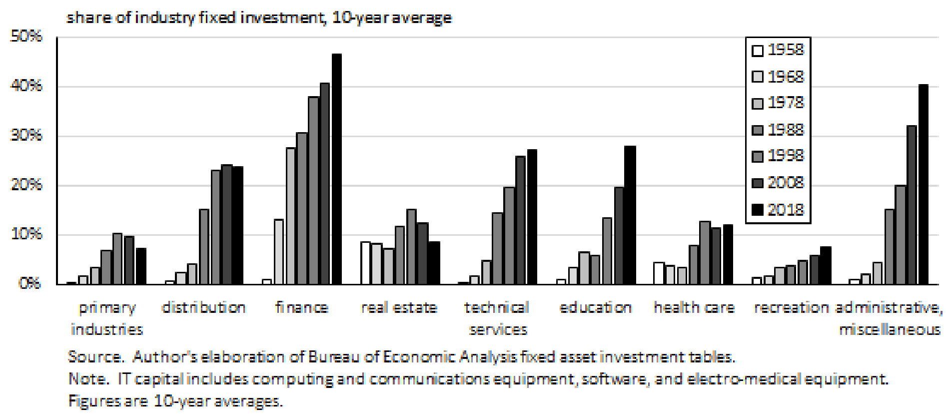


Source: Bureau of Economic Analysis.
Note: Business IT includes computing and communications equipment, software, and, for IT service industries, R&D. Consumer IT includes computers, peripherals, software, telephones, and other information processing equipment.

lowing page).[4] Across nearly all sectors, IT capital investment rose significantly from the 1950s through the 1990s, with an acceleration in many sectors in the 1980s and 1990s. Since that time, digitalization by this measure has leveled off in distribution—retail and wholesale trade, transportation, and warehousing—and declined outright in primary industries—manufacturing, mining, utilities, and agriculture. Meanwhile, digitalization has continued to climb in other sectors, with particularly sharp increases in financial, techni-

[4]In fig. 3 on the next page, sector definitions are as follows. Primary industries include agriculture, forestry, fishing, and hunting; manufacturing; mining; utilities; and construction. Distribution includes retail trade, wholesale trade, and transportation and warehousing. Finance includes finance and insurance. Real estate includes real estate and rental and leasing. Technical services includes legal services; miscellaneous professional, scientific and technical services; and motion picture and sound recording industries. Education includes educational services. Health care includes health care and social assistance. Recreation includes arts, entertainment, and recreation; and accommodation and food services. Administrative and miscellaneous includes administrative and waste management services; and other services except government.

Figure 3: U.S. IT Capital Investment by Sector



cal, and administrative services.[5] The financial sector remains the most IT-intensive sector outside of IT services and corporate management—the two sectors not shown in the figure—for which IT capital accounts for 53 percent and 79 percent of fixed investment in recent years, respectively. Thus, the flat path of the aggregate digitalization indicator obscures an ongoing shift toward IT investment outside of distribution and primary industries.

Several other noteworthy changes in the nature of digitalization have accompanied the shift in industrial composition of IT capital investment:

- *Increasing reliance on purchased IT services* IT capital services comprise the provision of telecommunications, computing, and the design of electronic and software systems. Each of these services has accounted for a rising share of purchased intermediate inputs in the private sector since the 1960s (fig. 4 on page 6). The share for computing services, including cloud computing, has surged in recent years. The share for design of IT systems, including custom software, has moved up sharply

[5]Shares in fig. 3 are calculated using general purpose electronics. That is, the measure of IT capital shown excludes special-purpose equipment, such as robots and medical imaging machines, which often contain substantial electronic content. This simplification is of little consequence to the contour of the figure for most sectors, but for the health care sector, where capital investment in general purpose computing and communications equipment is relatively low, much of the digitalization has entailed investment in medical equipment with heavy electronic content, such as imaging machines. IT capital combined with electro-medical equipment accounted for roughly 1/3 of fixed investment in the health care sector in 2018.

as well. Communications services, which accounted for the greatest share of IT intermediates the late 1990s, has retreated since then.

- *Radical increase in mobility* Mobile broadband subscription rates show smartphone use rose from minor at the time of the introduction of the first iPhone (2007) to pervasive in the United States by 2019 (fig. 4 on the following page).

- *Shift toward intangible investment* Digital economy investment has shifted toward intangible capital, which accounted for roughly 1/2 of IT investment in 2000 and now accounts for 2/3 of the total (fig. 4 on the next page).[6]

- *Ongoing explosion of data* Indicators of the volume of digital activity continue to rise. The stock of digital data, as indicated by sales of the hard disk and solid state drives which account for the bulk of digital storage, rose by a factor of more than 1,000 between 2000 and 2019 (fig. 4 on the following page). Exponential growth in data traffic has continued as well, as indicated by unrelenting increases in internet use (fig. 4 on the next page).

In the midst of this evolution in digitalization—troves of digital information, soaring internet use, and ubiquitous network access—a new business model has emerged: firms that assist business and household users in navigating the information landscape, which we'll call "digital platforms."[7] They provide a shared technological and business framework for this activity.[8] These firms are a large and growing share of the economy: Amazon, Google, and Facebook alone accounted for 1/2 trillion dollars in revenue in 2019, a ten-fold increase since 2009 (fig. 5 on page 7).

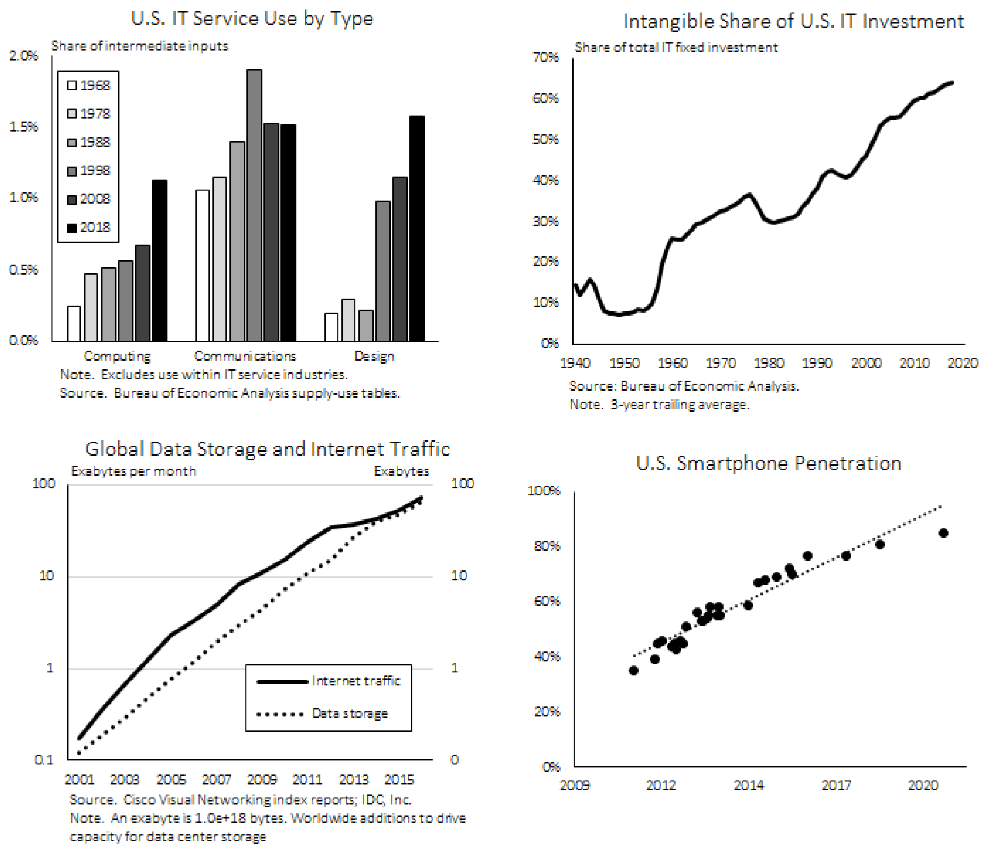
The core competency of these digital platform firms is efficient connection of users to information matching their needs using machine learning

[6]See discussion of this trend in Haskel and Westlake (2017), and Corrado (this volume).

[7]This is a broader concept than both the OECD's "online platforms" defined by West, Carblanc and Ferguson (2019)—focused on two-sided matching—and U.S. Department of Commerce's "digital matching firms" defined by Telles (2016)—focused on user-generated content.

[8]Note the distinction from the use of "platform" in the computing context—where operating systems are examples of platforms—and from the use of "platform" in a financial markets context—where a trading platform simply provides an efficient means of connecting two sides of a market.

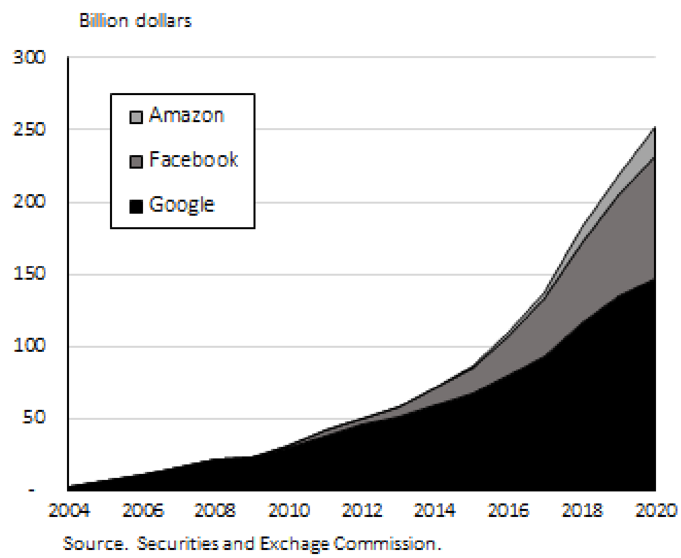
Figure 4: Indicators of Digitalization



algorithms and distinctive custom interfaces in the form of websites and smartphone apps. They often match business clients to information collected about their users as well. Their methods may be used to improve the matching process for items of almost any kind—goods, web pages, and images are examples—provided they can be digitally described. So, while these firms have varied product lines, they share a production process. In that sense, these companies constitute a distinct industry.[9] These firms are the core of the digital economy concept.

[9]NAICS (the North American Industry Classification System) endeavors to classify business establishments to industries according to "similarity of their production process" used to produce goods and services—the production function—rather than the output itself (Executive Office of the President and Office of Management and Budget, eds, 2022).

Figure 5: Digital Platform Advertising Revenue



In addition to their products, digital platform firms differ in other material but ancillary ways. For example, their revenue may come from facilitating targeted advertising or from charging users directly for services.[10] And, digital platforms may or may not own the items they index. Also, they may or may not own the IT capital essential for their service. (Netflix is run in great part using IT capital services purchased from cloud providers, for example.) Digital economy firms may also provide IT capital services, such as cloud computing, to households, to other digital platforms, and to firms of all kinds. But, the the *differentia specifica* these firms share is that they excel at matching users to information, often by use of artificial intelligence. That is, they push the boundaries of what seemingly human activities can be subsumed into and improved upon using mathematical methods, machine learning in particular, often in the form of prediction or recommendation software.[11]

[10] West et al. (2019) discuss an array of examples and provide a typology of online platforms.

[11] See the discussion of "recommendation engines" in Schrage (2020) and Resnick and Varian (1997). For a broader discussion of the economic effects of artificial intelligence, see Agrawal, Gans and Goldfarb (2019).

In summary, rapid digitalization has continued in recent years and the nature of digitalization has evolved. The share of IT capital in overall business and household investment has stabilized, but the economy is in the midst of a shift toward outsourced IT services. And, the emergence of digital platform firms at the center of the information landscape is a key feature of the latest era in the ongoing IT revolution.

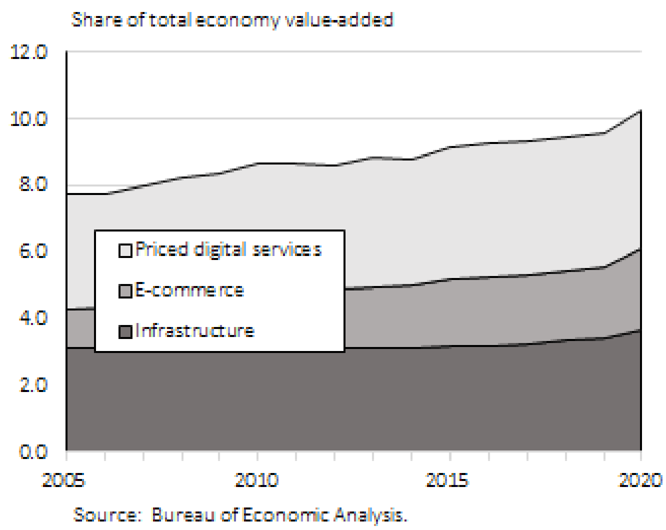
3 How big is the digital economy?

Discussions of the digital economy often leave its boundaries vague, and statistical agencies have wrestled with the task of making the concept precise enough to support quantification.[12] In the United States, the Bureau of Economic Analysis (BEA) has constructed a satellite account to supplement the core national income and product accounts (NIPAs) that provides a serviceable measure of the digital economy (**?**). It encompasses infrastructure (production of IT capital), e-commerce, and priced digital services (services related to computing and communications). In practice, approximately 200 products and services judged to be primarily digital are identified from the list of thousands of types of output in the input-output accounts produced by BEA. The output of these items is classified to priced digital services, e-commerce, digital media, and infrastructure production and a share of the value-added from industries producing these items is assigned to the digital economy. Even with highly granular output data in hand, creating such a satellite account is a difficult undertaking. Some cases are straightforward, such as the production of cell phones; other categories contain both digital and non-digital items and are excluded for lack of more detailed information. For example, ride-hailing services operating through digital intermediaries are excluded as they cannot be separated from conventional taxicab services (Barefoot, Curtis, Jolliff, Nicholson and Omohundro, 2018).

The BEA satellite account serves to demonstrate that the digital economy is a substantial and increasing share of the U.S. economy: Over the period

[12]As other treatments of the subject have observed, definitions of the "digital economy" vary or are absent in papers on the subject (Bukht and Heeks, 2017). And, studies with relatively clear definitions make the equally valid choice to refer to the scope of focus here as the "digital sector" (Reinsdorf and Quirós Romero, 2020) or the "digitalized economy" (Ahmad and Schreyer, 2016). We use "digital economy," in an effort to align with common usage in the United States (fig. 1 on page 2).

Figure 6: U.S. Digital Economy, NIPA Satellite Account



from 2005 to 2020, the share of the digital economy in total economy value added rose from 7.8 percent to 10.2 percent (fig. 6). Real value-added for the digital economy grew at an average annual rate of 6.1 percent over this time period, four times the rate of the total economy.

An international effort is underway to develop national accounting standards that will support consistent measurement of the digital economy over time and facilitate cross-country comparisons. In 2016, the G20 offered this guidance: "The digital economy refers to a broad range of economic activities that include using digitized information and knowledge as the key factor of production, modern information networks as an important activity space, and the effective use of information and communication technology (ICT) as an important driver of productivity growth and economic structural optimization" (G20, 2016). Interestingly, the definition is focused exclusively on the use of IT, not its production.

As a narrative description of the digital economy, the G20 guidance is useful, but to put the guidance into practice, one would need operative statements of just what constitutes a key factor of production, an important activity space, and an important driver of growth. In addition, key hurdles for full integration of the digital economy into the System of National

Accounts (SNA) are the additional detail on digital activity in supply-use tables, the measurement of digital international trade, and data collection from transnational entities which may not have suitable location-specific records to provide the information needed for national accounting (OECD, 2020).

Importantly, creating the measures needed to study the digital economy from a productivity analysis perspective may be a less demanding exercise than full integration of the digital economy into the SNA, as discussed next.

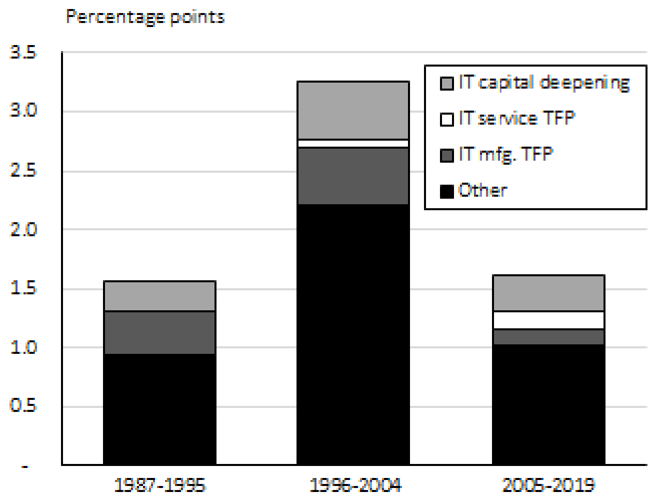
4 How much does the digital economy contribute to economic growth?

IT capital production and its use throughout the economy has played a major role in the contour of aggregate U.S. labor productivity growth in recent decades. This effect can be seen through the lens of conventional growth accounting: In the presence of competitive markets and constant returns to scale, economic growth at an aggregate level can be decomposed into contributions from inputs weighted by their income shares plus a contribution from total factor productivity (TFP), the efficiency with which inputs are combined to produce outputs (Solow, 1956; Hulten, 2010).

Using this approach, estimates from the Bureau of Labor Statistics (BLS) show the 1-1/2 percentage point rise in labor productivity growth in the mid 1990s can be attributed in great part to a rise in the contribution of IT, as can the fall back of labor productivity growth from the mid-2000s to the present (fig. 7 on the next page). In particular, the contribution from total factor productivity (TFP) in the IT capital producing industries moved up early in the IT boom, and in response to the corresponding fall in prices, IT capital investment increased as well. Subsequently, the contribution from TFP fell back dramatically, due to both an apparent fall in industry productivity and a reduction in the size of the domestic industry due to offshoring; IT capital deepening shrank as well. More recently, the contribution from IT service TFP, the white bar, has moved up and is now as large as the contribution from TFP in the production of IT capital. Outside studies echo this qualitative takeaway—a substantial rise in the productivity contribution of IT production and use and a subsequent drop—but many have found noticeably larger IT contributions.[13] Accordingly, the contributions shown in

[13]See Oliner and Sichel (2000); Jorgenson, Ho and Stiroh (2003); Byrne, Oliner and

Figure 7: Contributions to U.S. Labor Productivity



Source: Bureau of Labor Statistics.
Note: TFP is total factor productivity.

official estimates are best seen as somewhat conservative.

As discussed above, the activity of digital platform firms is a prominent feature of the post-2005 period, when the contribution of IT to productivity stepped down in the conventional growth accounting discussed above. While the contribution of substantial IT capital services *used* by these firms is captured in the conventional growth accounting in fig. 7, the contribution from TFP growth in these firms is not. That is, to the extent that business practice innovations at Google, Facebook, and Amazon have led them to use IT capital (and other inputs) more efficiently, extracting more value-added out of a given stock of software, computing equipment, and communications equipment, the contribution of the digital economy to economy-wide labor productivity growth is not captured. A growth accounting framework that includes this contribution is provided in the box, "Digital Economy Growth Accounting."

The growth accounting approach quantifies the sources of growth but admittedly provides little in the way of explanation. The process by which TFP growth is achieved—–through innovation in production techniques, their

Sichel (2013) For analysis of other countries, where the story is somewhat different, see Van Ark, Inklaar and McGuckin (2003) and Gordon and Sayed (2020).

spread through the economy, and through reallocation of resources to more productive firms——is not addressed.[14][15] Nor is the connection between TFP growth, the prices of capital goods, and capital deepening made explicit. Nevertheless, it serves as a useful organizing framework. This simple formulation allows us to isolate the role of TFP growth in firms producing IT capital, the knock-on effect of investment in IT capital and the services produced by that capital (whether delivered by the firm's own capital stock or purchased at arm's length) and the contribution from innovative platforms, which mediate interactions with the trove of information that is a byproduct of digitalization. As a practical matter, accounting for the digital economy in a growth accounting framework requires measurement of the components of equation eq. (5) on the next page: prices and value-added for each producing sector as well as factor incomes and capital services for each capital type, and, of course, an accurate measure of GDP. We turn to the feasibility of meeting these requirements in the next section.

Digital Economy Growth Accounting

Modelling production as a function of capital services, labor inputs and a scale factor, μ, representing total factor productivity (TFP), $Y = \mu F(K, L)$, the growth rate of output per hour worked, $\dot{y} = \dot{Y} - \dot{H}$, is a linear combination of TFP growth and the growth in inputs, weighted by their income shares, α_K and α_L:

$$\dot{y} \quad = \quad \dot{\mu} + \alpha_K \dot{k} + \alpha_L \dot{Q}, \tag{1}$$

where $\dot{k} = \dot{K} - \dot{L}$ represents capital deepening and $\dot{Q} = \dot{L} - \dot{H}$ represents labor quality growth. Extended to account for distinctions among types of capital, we distinguish IT hardware, T, IT intangible capital, N, and other capital, C:

$$\dot{y} = \dot{\mu} + \alpha_T \dot{t} + \alpha_N \dot{n} + \alpha_C \dot{c} + \alpha_L \dot{Q}. \tag{2}$$

[14] Akcigit and Ates (2021) discuss and frame the literature on innovation and business dynamism. Samuels and Ho (2021) estimate the contribution of reallocation to economic growth.

[15] Note that growth accounting is silent on the process by which IT use raises productivity. Goldfarb and Tucker (2019) elaborate on the many ways the use of IT reduces costs, including search, replication, transportation, tracking, and verification and discuss the literature on these aspects of digital economics. Growth accounting abstracts from these details and simply measures the apparent contribution in the aggregate.

Digital Economy Growth Accounting (continued)

Decomposing total output into the sum of the value added of IT capital goods industries mentioned and the output of digital platform services, P, and all other goods and services, X, and assuming each sector produces according to a production function with separable TFP,

$$\dot{\mu} = \delta_T\dot{\mu}_T + \alpha_N\dot{n} + \delta_N\dot{\mu}_N + \delta_C\dot{\mu}_C + \delta_P\dot{\mu}_P + \delta_X\dot{\mu}_X, \tag{3}$$

where the weights, δ, correspond to the gross output of the sector divided by aggregate value-added for the economy (Hulten, 2010).

The contribution of digitalization—the use of electronics and IT intangibles throughout the economy—to productivity is accounted for through $\alpha_T\dot{t}$ and $\alpha_N\dot{n}$ respectively.

Productivity growth in the electronics production sector, weighted appropriately, $\delta_T\dot{\mu}_T$ contributes directly to aggregate productivity, as does productivity growth in the IT intangibles sector, $\delta_N\dot{\mu}_N$.

The contribution of digital platforms, is captured by the Domar-weighted TFP for the industry, $\delta_P\dot{\mu}_P$ Importantly, this is not the contribution of the intensive use of IT capital by digital platforms—captured in the capital deepening terms—but rather the increasing efficiency with which they combine IT capital services with other inputs to deliver services valued by users.

Thus, the contribution of the digital economy to labor productivity growth, $\dot{y}_D$, can be formulated as the sum of the contribution from IT capital production—both tangible and intangible—the contribution of IT capital deepening, and the contribution of the productivity of the digital platform industry:[a]

$$\dot{y}_D = (\delta_T\dot{\mu}_T + \delta_N\dot{\mu}_N) + (\alpha_T\dot{t} + \alpha N\dot{n}) + \delta_P\dot{\mu}_P \tag{4}$$

In the presence of competitive markets and stable input prices, the growth rate of industry TFP will be well proxied by the negative of the growth in the price index. Thus, the contribution of the digital economy to economic growth can be written equivalently in terms of prices.

$$\dot{y}_D = -(\delta_T\dot{\pi}_T + \delta_N\dot{\pi}_N) + (\alpha_T\dot{t} + \alpha N\dot{n}) - \delta_P\dot{\pi}_P. \tag{5}$$

Digital Economy Growth Accounting (continued)

[a]This accounting omits the effects of spillovers from the digital economy, such as network effects. On that subject, see Corrado, Haskel and Jona-Lasinio (2017); Corrado (2011); Gordon and Sayed (2020).

5 Can we measure the digital economy with the statistics available?

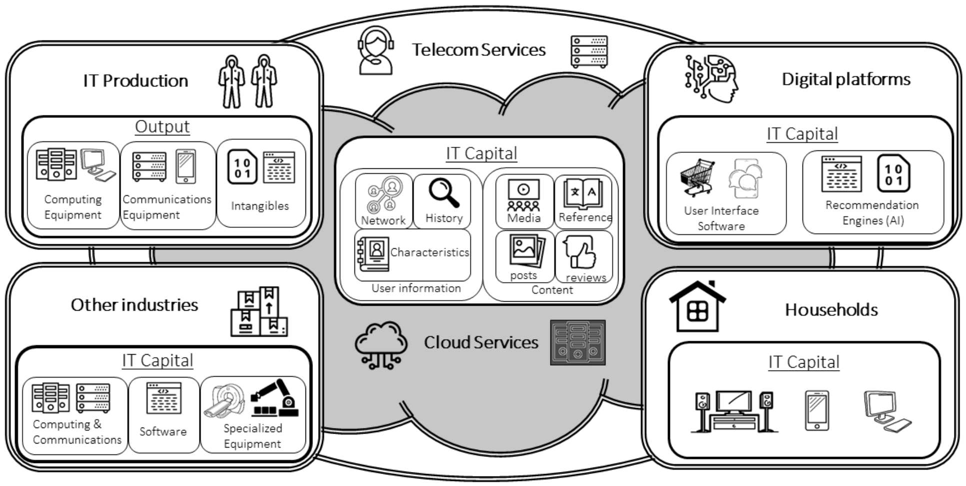
The schematic in fig. 8 on the following page provides a framework for discussion of measurement issues, dividing the economy into six sectors: the IT production, digital platform, household, and residual "other industries" sectors are connected by a telecommunication services sector, and all five of these use the services of cloud providers.[16] (Recall that industries and sectors are collections of establishments—plants, offices, data centers, and so forth—with a common production process, and firms may span multiple sectors.) Each sector has a distinctive mix of tangible and intangible IT capital. Our task is to locate and measure in these sectors the three contributions to productivity from the digital economy: TFP in IT capital production, TFP in digital platforms, and the use of IT capital services throughout the economy.

Production of IT equipment takes place primarily in the IT production sector and its measurement centers around the construction of constant-quality production price indexes for the output of these products, a difficult but well understood area of measurement.[17] The state of play in measurement of IT equipment is discussed briefly in the box, "Measuring Data Processing Equipment," and in an appendix.

[16]Loosely, the telecom and cloud sectors encompass the internet. For a detailed look at the internet and the associated markets, see Greenstein (2020)

[17]Other sectors engage in in-house production of their own hardware and software. While this own-account software and R&D is captured in GDP as investment, own-account equipment manufacturing is not. A substantial share of data center computing capacity is attributed to a small number of firms, such as Amazon and Google, who often build data centers from purchased electronic components, leading to the omission of much of their computing and communications equipment (Byrne, Corrado and Sichel, 2018a).

Figure 8: Digital Economy Schematic



Measuring Data Processing Equipment

The role of electronic data processing in the economy has been top of mind for economists since the late-1990s surge in U.S. productivity, exemplified by Dale Jorgenson's 2001 American Economics Association presidential address, which noted the productivity boom was driven in great part by the manufacture and use of data processing equipment and software (Jorgenson, 2001). And, long before the effect of data processing on productivity came to the foreground, economists had begun to account for the rising efficiency of computing and communications in research on price trends and to incorporate falling price-to-performance ratios for computers into economic statistics (Chow, 1967; Cartwright, 1986). The Bureau of Economic Analysis, in collaboration with IBM, introduced performance-adjusted price indexes to the national accounts for computing equipment in 1985, with coverage beginning in 1972. Later work pushed coverage back to 1959.

Price Index Research Quality and U.S. Relative Importance
by Type of Data Processing Equipment[a]

Measuring Data Processing Equipment (continued)

Equipment type	Quality	Investment	Consumption	Production
Computing		28.1	35.8	9.7
Computers	Good	19.3	21.7	4.3
Storage	Good	1.8	2.9	2.3
Other	Poor	7.1	11.2	3.2
Communications		39.1	26.6	16.7
Switching	Good	8.9	NA	1.0
Transmission	Good	6.0	NA	9.6
Mobile phones	Good	12.8	25.9	0.4
Other	Poor	9.9	0.7	5.7
Special-purpose	Poor	29.7	47.4	73.6

The author's judgmental assessment of research quality is provided in the table (See elaboration in the appendix). General purpose computing and communications equipment is fairly well measured, but other (peripheral) and special-purpose equipment is not. Loosely speaking, computing, communications, and special-purpose equipment play comparably-sized roles in household and business spending on data processing equipment, so getting measurement right for all of them is important. Despite extensive research on the subject, roughly 50 percent of U.S. investment, 60 percent of U.S. consumption, and some 80 percent of U.S. production of electronic equipment is measured using price indexes with little to no supporting research verifying their ability to separate quality change from inflation.

[a] Shares for 2017. Share of investment and consumption from based on data from Bureau of Economic Analysis with breakdown by communication equipment type from Byrne and Corrado (2017). Component shares based on data from Reed Electronics and Semiconductor Industry Association. *Note:* "NA" is "not applicable."

Measurement of intangible capital, broadly speaking, is discussed in Corrado (this volume). Our focus below is on its particular character in the digital platform industry. Digital platforms produce, purchase, or accumulate from users intangible capital (content), such as media files (Netflix), reference information (Wikipedia), social media posts (Twitter), and reviews (Yelp). And, in the course of business, platforms accumulate information *about* users, such as who is in their social network, the history of their behavior on the platform, and other characteristics. The industry focuses on the creation of "recommendation engine" software—a kind of intangible capital—which takes take user queries, combines them with content characteristics, information on the particular user, and information about their user base as a whole to predict the content likely to match the user's needs using machine learning (Schrage, 2020; Resnick and Varian, 1997).[18] Business clients query the platforms as well, seeking in many cases the users most suited to their products, initiating a similar recommendation process. The interface with the recommendation engine, which may take the form of a mobile phone app, a website, or an API (application program interface), is a critical component of the platform's intangible capital as well. Each of these—information on content and users, recommendation engines, and the interface used to access it—is a stock of intangible capital which provides a stream of capital services used as an input to the production of platform services (fig. 8 on page 15). The total factor productivity contribution from the digital platform industry is their ability to efficiently combine these intangibles with general-purpose IT capital—computing, communications, and software—and other inputs. At times, the distinction between the capital services of the custom software created by the business and the TFP of the enterprise is not entirely clear. Business practices for a firm, for example, which raise the efficiency with which inputs are combined (i.e. TFP), can be treated as intangible capital as well and may be encoded in the software.

The productivity measurement challenges posed by digital platforms are discussed below. We focus on output, investment, consumption, and trade, all of which are needed to calculate the contribution of the digital economy to growth and productivity.[19] Accurate measurement of the output of the digital platform industry is needed to calculate its TFP. Accurate investment is needed to estimate the capital stock and associated service flows, thereby the contribution of the use of IT capital to productivity. And, capturing consumption and trade accurately is needed to get the measurement of overall

[18]Machine learning (ML) is used in a wide range of other contexts as well, but its use is not sufficient for a firm to be a digital platform. Kleinberg, Lakkaraju, Leskovec, Ludwig and Mullainathan (2018) consider their potential for use in the criminal justice system, for example. If software is measured accurately, the contribution from ML in those industries should be captured by the capital deepening component (IT use) of growth accounting.

[19]The public sector is not generally included in the scope of the digital economy. However, government R&D plays a major role in the digital economy value chain.

GDP right. Among the problems faced in measuring these flows are the value of consumption and intermediate use of services without market prices, the valuation of investment in databases and highly customized software, and locating these platform firms and their establishments within the current industry classification framework to accurately capture their output.

5.1 Output

To identify the output of the digital economy, and digital platforms in particular, we must go from the tacit definition of the digital economy in fig. 1 on page 2—a set of companies—to a rules-based definition applicable to establishments, preferably one based on the variables found in existing micro-data. As noted above, the common characteristic that sets digital platform firms apart——their core competency——is mediation between actors seeking information about products and services and about each other by use of machine learning. This essential activity constitutes a production function-based definition of an industry—the approach recommended by NAICS (the North American Industry Classification System)—but no such industry has been included in NAICS thus far. That being said, NAICS has evolved since its introduction in an effort to remain relevant in the midst of rapid digitalization and it is possible to identify NAICS industries that appear likely to contain digital economy establishments. These are provided for each vintage of NAICS in an appendix, illustrating this evolution.

However, even if NAICS were to include a "digital platforms" industry, because establishments are typically assigned to the industries of their primary revenue-generating activity and the output of digital platforms is often unpriced, digital platform industry establishments may well be scattered across the industries associated with their primary source of revenue. Consequently, to study the contribution of the digital economy to growth and productivity, it will likely be necessary to supplement NAICS-based micro-data to isolate the digital platform industry. For example, one could merge an outside list of digital platform companies with the Census Business Register to identify their establishments. The subset of these establishments excluding those devoted to other activities, such as hardware production, would constitute a first pass at delineating the digital platform industry. Further refinement may be possible by leveraging the information contained in the American Business Survey (ABS) on technology characteristics of businesses. In particular, ABS respondents were asked if their firm employed machine learning (in 2018) and artificial intelligence (in 2019). The share of firms employing these technologies is quite small: Employer firms using machine learning for 5 percent or more of their production represent 4.6 percent of sales or revenue in the 2018 survey (Zolas, Kroff, Brynjolfsson, McElheran, Beede, Buffington, Goldschlag, Foster and Dinlersoz, 2021).

A successful effort of this sort would provide a foundation for measuring the contribution of TFP growth in digital platform industries to aggregate productivity. Much the same as in the IT production industries, a crucial next step will be constructing constant-quality price indexes to calculate real output by deflating the nominal output of the identified establishments. A key source of revenue for many digital platform firms is advertising, the value of which is large and growing rapidly, as shown in fig. 5 on page 7. The more accurately this revenue is adjusted to account for quality change—by the use of constant-quality price indexes—the more of productivity growth may potentially be attributed to the digital economy. Over time, recommendation engines likely improve in their ability to uncover latent preferences and steer advertisers to the consumers most suited to their products. Hence, a given nominal value of advertising may correspond to higher quality as recommendation technology improves. Moreover, as discussed below, it will also be necessary to tackle the question of valuing the output provided to households for which there is no associated revenue.

5.2 Investment

Real capital service flows are essential for productivity analysis—for measuring the contribution of the use of IT to economic growth—and valuing the types of tangible and intangible capital stock depicted in fig. 8 on page 15 (and the associated investment, depreciation, and service flows) is an active area of research with a variety of empirical approaches. We focus on intangible investment in the digital platform industry. Investment in tangible IT capital is amenable to a standard approach—nominal spending divided by a suitable price deflator—and is discussed briefly in an appendix. Intangible investment, broadly, is discussed in Corrado (this volume).

Measurement for intangibles is especially difficult when the asset is created within the firm. Investment in purchased intangibles, such as software and R&D services, must be adjusted for quality change by deflating by an appropriate price index, which can be difficult to construct.[20] But, "own-account" assets do not even have a nominal purchase price. The standard approach in this case is to impute the value of investment as a share of the wage bill for related job families. One might assume, for example, that one-half of the hours worked by a software engineer is devoted to creating software that will deliver services over a lengthy period of user time. The cost of production for the software, then, would be equal to half the value of her compensation. While such an approach can be taken for digital platform firms (this approach is, in fact, used in the NIPAs), a portion of the time spent creating the intangible capital held by digital platforms is provided by users, leading this sum-of-costs methods to understate its value. Estimates are available of this understatement, though their magnitudes depend critically on the valuation of time. Nakamura, Samuels and Soloveichik (2018) provide estimates of user-generated content valuing the activity based on their estimate of the implicit earnings of viewers watching television, which are quite modest. Goolsbee and Klenow (2006) use the average wage to value user activity, arriving at a valuation several times larger, highlighting the unsettled nature of this topic.[21] Brynjolfsson, Kim and JooHee (2013) leverage the relationship between user activity—time spent, posts, and comments—and firm value to calibrate a general equilibrium model and arrive at an estimate of the value of user-generated capital for a subset of digital platforms, namely internet-exclusive media firms, concluding that user-generated capital accounts for 60 percent of the value of these firms. Demonstrating a different approach, Ewens, Peters and Wang (2019) use of prices paid for corporate acquisitions and the valuation of their tangible assets to arrive at a value for intangible assets as a residual, which they use to calibrate the model developed by Corrado and Hulten (2010). They arrive at a valuation of economy-wide intangibles moderately lower than found in the NIPAs, but moderately higher for high-tech firms.

Thus far, not all intangible assets have been capitalized in the NIPAs; software, R&D, artistic originals, and mineral rights are currently included;

[20]On progress at BEA and elsewhere measuring prices for intangible investment, see Aizcorbe, Moylan and Robbins (2009) and Corrado (this volume).

[21]Such "free investment" issues are not confined to the digital platform industry. Greenstein and Nagle (2014) points this out as an issue with open source software. As Greenstein notes, programmers are wont to spend leisure time on this sort of activity. Using the example of Apache web server software, the authors demonstrate this is an issue large enough to worry about.

importantly for our purposes, data is not. Rassier, Kornfeld and Strassner (2019), noting that databases—a form of software—are treated as investment in the current SNA (System of National Accounts) standard, but the data embedded in the database is not, propose an approach to capitalizing the information content based on SNA principles.[22] Crucially, naturally occurring data generated as a by-product of other activity and collected at low cost is excluded, as is user-generated personal data held by firms but not used for production purposes. These exclusions are particularly salient for digital platforms.

5.3 Consumption

Household consumption of the output of the digital economy includes digital network access services, the capital services of the IT equipment held by the household, and intangible services from digital platform companies

5.3.1 Digital network access services

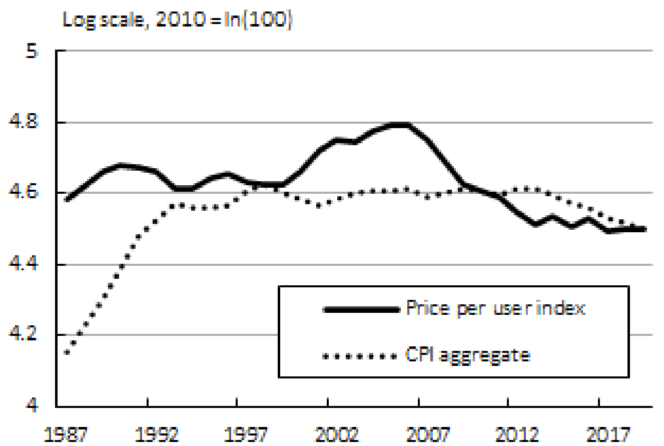
Digital access services include telecom, internet, streaming, cable television, and cloud services. Official U.S. prices for consumer digital access services as a whole (the dotted line in fig. 9 on the next page) have moved sideways, on balance, in recent years, implying the quality of services received by households per dollar spent changes very little over time, a somewhat surprising result in a world seemingly filled with digital service innovation.[23] For comparison, Byrne and Corrado (2019) construct a price index with *no adjustment for quality*, aggregating the raw average monthly price paid by households for each of the services and get a similarly flat index (the black line).

For these services, choosing the unit of analysis turns out to be crucial to measuring consumption. Byrne and Corrado (2019) examine data for the United States and find that data use per telecom service contract has soared in recent years while contract prices have been fairly stable, thus

[22] In practice, the approach to estimating R&D and software in the NIPAs—allocating a portion of the wage bill for related occupations—may capture some investment in data as well.

[23] The aggregation of official prices reported in Byrne and Corrado (2019) is shown.

Figure 9: Prices for digital access services.



Source. Byrne and Corrado (2020); Bureau of Labor Statistics.
Note. Price per user index is Byrne and Corrado calculation of total service spending divided by users for smartphone, feature phone, internet access, cable, and three video streaming services weighted by spending from NIPAs.

quality-adjusted prices for telecom services have plunged.[24] In contrast, official prices use price *per contract* and the CPI for a mobile phones—even though hedonically adjusted—yields a noticeably slower falling price index than does pricing per unit of data consumed. Similarly, for video streaming services, if the value of Netflix, say, is invariant to the number of shows actually watched, official prices seem accurate, but if programming consumed is the proper measure of consumption, prices have plunged in recent years. In effect, in the NIPAs consumption of streaming services is the same for a subscriber *regardless of the number of programs watched*. Edquist, Goodridge and Haskel (2022) examine music streaming services accounting for volume of use and find a striking overstatement of inflation. Cloud services, consumed primarily by firms as an intermediate input for production, but also by households (to store photos and documents, for example) have readily available data, and Byrne, Corrado and Sichel (2018a) construct price indexes for several kinds of cloud services and find steeply falling prices as well. All told, official and alternative prices are markedly different.

[24] Abdirahman, Coyle, Heys and Stewart (2020a,b) find similar results for the United Kingdom.

Importantly, the economic relationship between the flow of real capital services and investment over time, via the rate of depreciation and the rate of interest, provides an opportunity to check for mutual consistency in the measurement system (Jorgenson, 1963) and shed light on this problem. Byrne and Corrado (2019) find that prices for digital access services fall over time at a similar rate to the price index for the related capital, on average, the consonance we expect from capital theory.

5.3.2 Household IT equipment services

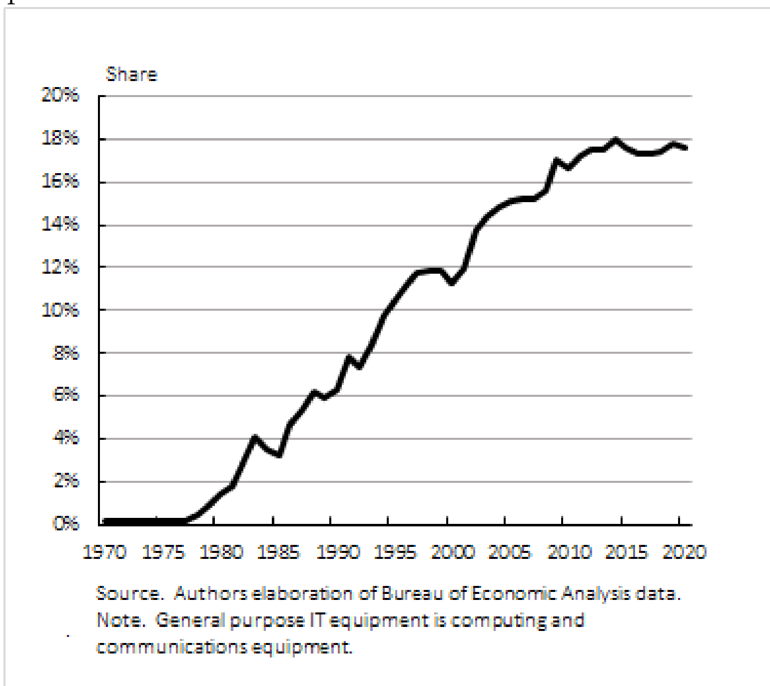
In conventional national accounting, IT equipment purchased by the household is treated as consumption although, much like housing, which is treated as investment, it is a capital good that provide a stream of services over time. The argument for the differing treatment is that the trend and cyclical variation of GDP may be noticeably distorted by household movement between owning and renting residential property while there is assumed not to be a similar issue for other household assets, such as motor vehicles and IT equipment. However, as the household share of spending on IT equipment has risen over time (fig. 10 on the following page), the increasing understatement of IT capital services in the economy is potentially significant from the perspective of productivity analysis of the digital economy. Byrne and Corrado (2019) calculate the effect of capitalizing this equipment and find an increasing effect on GDP growth in recent years, from a contribution of .05 percentage points in the 1997-2007 period to .15 percentage points in the 2007-2017 period.[25]

5.3.3 Digital platform services

Counting the services of digital platforms as consumption is a somewhat contentious issue, as they are to a great extent delivered for free, at least to households. Groshen, Moyer, Aizcorbe, Bradley and Friedman (2017), note that consumption of these services is nonmarket activity properly excluded from GDP and that, in any case, one may reasonably expect the cost of production of these services is to be reflected in the price of final goods if these platform firms are to remain solvent—Facebook receives advertising revenue

[25]See discussion of alternative approaches to capitalizing consumer durables in Katz (1983) and the vision of more complete, mutually consistent national accounts in Jorgenson and Landefeld (2007).

Figure 10: Household share of U.S. spending on computing and communications equipment.



and the price of the advertised product will reflect that cost. Although one may expect GDP to move sympathetically with the free consumption as a result, serving as an *indicator* of the free household consumption, it remains the case nevertheless that the households consume *both* the final good *and* the free digital platform service, which is not counted as consumption.

A variety of approaches have been proposed to take account of free consumption in GDP. An emerging direct approach to determining the valuation of free services is to conduct experiments designed to elicit participants' willingness to pay. Brynjolfsson, Collis, Diewert, Eggers and Fox (2019) fold this approach into national accounting to provide a method of constructing an expanded measure of GDP.

Naturally, imputing a value for household consumption of free services implies that corresponding income must be imputed as well, expanding the boundaries of GDP as conventionally constructed. Objections to doing so include the fundamentally different nature of income that cannot be divided between consumption and savings or indeed among a range of alternative consumption choices. Furthermore, income counted in the SNA is restricted to "income arising from involvement in processes of production or from ownership of assets," neither of which is the case when free services are consumed unless once considers surfing the world-wide web, say, as employment. Nakamura, Samuels and Soloveichik (2018) do just that, modelling this consumption as implicit exchange through barter of time spent viewing advertisements.[26]

5.4 Trade

Digital economy exports—typically services in the case of the United States—and imports—typically goods, are challenging to measure as well and potentially distort the contribution of the digital economy to growth and productivity. We consider two examples.

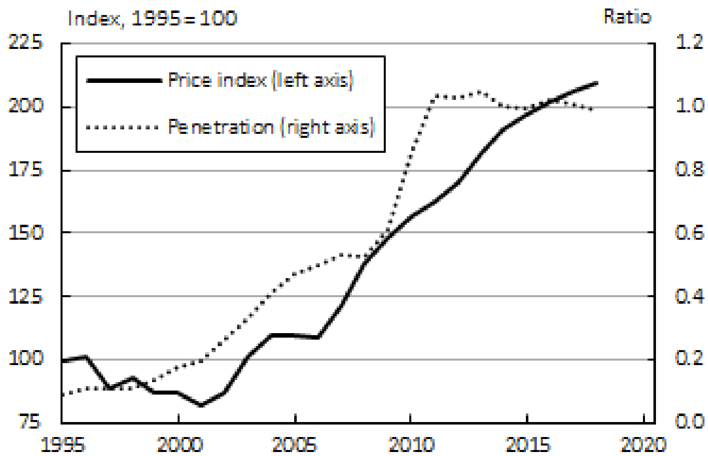
Contrasting the price index for imports to the price index for consumption raises concerns about consistency in the measurement system (fig. 11). A massive shift in U.S. spending on computing equipment toward imports occurred from 2000 to 2010, when import penetration rose from minimal to nearly complete (the dotted line). At the same time, the ratio of the U.S. import price index to the (domestic) producer price index, an indicator of the relative price of imports, roughly doubled (the solid line). A tension of this magnitude between relative prices and consumer behavior sustained over a long period—a pronounced shift toward a higher priced alternative—is puzzling. Although other factors may be in play, this tension suggests the presence of inconsistent price measurement across the separate BLS programs that produce prices for imports and domestic production.[27]

A substantial portion of the value-added in this IT equipment produced abroad is the value of design and management taking place in the United States, but the associated U.S. export may well omit quality improvements embedded in designs. How such service exports are measured has been the

[26] This exchange takes place in traditional retail settings as well, where personalized experiences are more prevalent than online: Soloveichik (2018) finds that brick-and-mortar retailers have increased the value of free experiences provided, perhaps in response to competition from e-commerce.

[27] As Byrne and Pinto (2015) point out, it also raises the question of whether using a blend of import prices and producer prices to deflate investment spending, as is done in the NIPAs, is a sound approach.

Figure 11: Relative price of imported computers and import penetration.



Source: Bureau of Labor Statistics, Bureau of Economic Analysis, Census Bureau.
Note. Computer import price index divided by producer price index. Ratio of imports to production plus net imports.

subject of recent scrutiny.[28] U.S. "factoryless manufacturing" establishments—those that outsource the fabrication of products but maintain control of the production process, own the associated intellectual property, and bear the entrepreneurial risk—are classified to wholesale trade in official statistics (Murphy, n.d.). And, while the NIPAs are not sufficiently granular to determine with certainty what price index is used to deflate exports from these establishments, wholesale trade prices do not, as a rule, behave in a way that suggests noteworthy quality change: The official price index for the output of the wholesale trade sector moved up 2 percent, on average, in the 10-year period ending in 2018. In effect, absent intervention to ensure the real value of exports includes the value of domestically produced design improvements, the entirety of quality change in electronic equipment may well be implicitly attributed to greater efficiency in offshore assembly activity.

Interestingly, the first example suggests that IT imports are understated and the second example suggests IT exports are understated. The net effect of these two distortions may be either that GDP is overstated or that it is understated. In either case, the contribution of the digital economy is

[28]See the discussion of this activity in Doherty (2013), Kamal, Moulton and Ribarsky (2013), and Bayard, Byrne and Smith (2015)).

mismeasured.

6 Conclusion

Digitalization of the economy has continued in recent years, though the nature of digitalization has evolved. The latest wave of the IT revolution is characterized by radical mobility, greater emphasis on intangible capital, an ongoing explosion of data, and the machine-learning-based digital platforms that help users—both households and firms—navigate this landscape. An up-to-date notion of the digital economy must encompass all of these elements. With that definition in hand, we can unpack the impact of IT using growth accounting and ask if that impact has faded, but only after daunting measurement challenges are overcome. Among these are valuation of intangible assets and their services, accounting for technical change in IT equipment, and grappling with whether the boundaries of GDP in national accounts serve us well in the pursuit of the answer to this question. An array of techniques, reviewed in this chapter, provide leverage for measuring the digital economy. Each requires maintained assumptions to make progress—starkly illustrated when we assign a value to free services and unpriced intangible assets. Importantly, assumptions are in the nature of measurement for all economic statistics; we should not be shy about adopting them—if they are reasonable—when they help us make progress on the question at hand.

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Appendix A Measurement of Electronics

Measures of the production of, consumption of, investment in, and trade in IT equipment have received a great deal of attention in economic research, but many shortcomings remain unaddressed in the current statistical system. In this appendix, we review the state of play in the field. IT equipment includes of equipment devoted to the collection, storage, transformation, transmission, and reporting of data, namely:[29]

- *computing equipment*, including computers proper, data storage equipment, and the peripheral equipment used for data collection, reporting, and signal processing;
- *communications equipment*, encompassing the wireline connection of computing equipment in local area networks and over the internet, long-haul and local data transmission equipment, and cellular and other wireless systems;
- *special-purpose equipment* with embedded data processing capability, such as electro-medical and navigational equipment; and
- *components*, most notably microchips (semiconductors), but also circuit boards and other components, measured separately to identify the sources of innovation in final equipment and to measure trade flows.

A.1 Accounting for Quality

Official price indexes are most often calculated using a matched-model approach: Prices for goods in a representative basket are observed repeatedly over time and, each period, the price changes for individual items are averaged using weights reflecting their relative importance for the flow of interest, such as consumption or investment. Under the maintained assumption that the quality of each individual item in the basket is invariant over time, the price index thus created often provides a serviceable indicator of

[29]In addition to these measurement issues pertaining to specific products, there are issues of systemic consistency of measurement across products, countries, and time as well as boundary issues related to the use of data processing, some of which are discussed in the main text.

aggregate price trends, particularly when the product market is competitive and observations are reasonably frequent.

However, in the case of data processing equipment, product turnover and imperfect product market competition often present a challenge for the matched-model approach. New models typically embody differences in quality relative to existing models, such as engineering improvements or other design changes valued by the user, and may enter the market at a lower quality-adjusted price—such as a higher performance new model phone with the same nominal price as the previous model. In the presence of sufficient competition, such that the "law of one price" applies, the prices of incumbent models can be expected to fall, leading the workhorse matched-model index to capture the correct price trend through the growth rate of the incumbent models. Thus the index accounts for quality change indirectly.

But, for product markets characterized by imperfect competition—such as when cost of switching between products or platforms creates market power—price declines for incumbent items may not capture the full difference in quality. For example, captive users of older systems may pay more for their equipment on a quality-adjusted basis. Markets for electronics have often fallen into this category.[30] In such cases, supplemental analysis is needed to attribute a portion of the premium or discount for the new item relative to incumbent items to a difference in quality, leaving the residual as a measure of pure price difference.

This supplemental analysis often takes the form of imputing the price for a new product in the period just prior to its entry. The price change between the imputed price and the first observed market price is then folded into the matched-model index calculation, thus reducing the reliance on the induced price change in incumbent models for capturing quality change. In some circumstances, a menu of option prices is available with which one can construct this hypothetical price in the pre-entry period. Personal computer manufacturers often provide system "configurators" on their websites, for example. However, as **?** notes, discussing motor vehicles, "only a few of the observed quality changes come in discrete lumps with an attached price tag." The alternative is to impute a counter-factual pre-entry item price using a formal hedonic regression, leveraging the correlation of item prices with observed product characteristics.[31] Provided the qualities valued by the

[30] See the discussion of the computer market in Dulberger (2007), for example.

[31] Triplett (2004) and Aizcorbe (2014) provide detailed discussions of alternative ap-

user, both observed and unobserved, are correlated with the characteristics observed by the statistician, this approach can be expected to perform well. The clock speed of a computer processor, say, may serve as a proxy for a set of unquantified characteristics of interest to the consumer.

A.2 Progress with Conventional Analysis

Improvements in the measurement of electronic equipment prices made in recent decades at statistical agencies have included refinement of product classification systems, more frequent refreshing of the items in survey baskets to include new products, use of supplemental analysis such as hedonics to capture the value of new items, and in some cases adopting prices from outside research.

Personal computers (PCs) and mobile phones are prominent examples of successful construction of constant-quality price indexes. However, other products have received less attention, often due to data limitations, unobserved key quality characteristics, or market structures that make quality adjustment difficult. An impressionistic assessment of the state of play for quality adjustment is provided here followed by a discussion of avenues for further progress.[32] Here, our primary focus is on what remains undone, rather than an exhaustive review of the literature.[33]

- **Computing equipment**: Computer prices, especially PCs, have been the subject of a great number research studies, making them an exemplar for the practice of quality-adjustment.[34] Many statistical agencies devote particular attention to them; for example, NIPA prices for computer consumption, investment, production, and trade employ the price indexes constructed by the Bureau of Labor Statistics (BLS), which use detailed hedonic analysis to adjust for quality. The concerted effort exerted to get these prices right notwithstanding, corroboration of the

proaches to hedonic price index construction.

[32] For a synthesis of research on data processing equipment prices for the U.S. market, the reader is referred to Byrne and Corrado (2017) for investment prices and to Byrne and Corrado (2019) for consumption prices. For a comparison of the price indexes across countries, see Ahmad, Ribarsky and Reinsdorf (2017).

[33] Not covered here are electronic components, including chips, boards, and the subassemblies used in equipment of all kinds.

[34] See, for example, Berndt and Rappaport (2001), Chwelos (2003), and Pakes (2003).

results from outside research is needed on several fronts:[35]

- Is the recent marked slowing in official computer price declines confirmed by analysis of other data sources? Relative to 2005-2009, BLS computer price indexes for 2015-2019 fell, on average, 9 percentage points, 22 percentage points, and 4 percentage points slower for consumption, production, and imports, respectively.
- Is the BLS producer price index (PPI) for computer storage equipment, used for deflating investment, suitable for that purpose, in that it has edged down only slowly in recent years? A private consultancy, IDC, Inc., reports storage equipment prices (per megabyte) plunged in 2015-2019 an average of 24 percent and 37 percent per year for hard disk drives and solid state drives, respectively, while the PPI for storage equipment only edged down 1 percent per year on average during that period.[36]
- Are the technical advances embodied in cloud computing—greater utilization rates through load-levelling, more rapid task performance, electrical efficiency—captured in computer investment prices? This is a particularly challenging area for measurement in light of the practice used by some cloud providers of assembling data centers on site with purchased components, with the result that a market price is never observed for the completed equipment.
- Is more attention needed to computer peripheral equipment investment prices? The PPI used to deflate computer peripheral investment moved down at a 3 percent annual rate, on average, for 2015-2019, yet the consumer price index (CPI) for televisions, which are quite similar to terminals, fell 18 percent per year. And, Aizcorbe and Pho (2005) found prices based on retail scanner data fell significantly faster than official indexes for an array of peripheral types.

• **Communications equipment**: Communications equipment prices have been studied extensively as well, with particular attention to the

[35] Regular publication of the results of the hedonic calculations behind BLS prices would aid that effort.

[36] An alternative index based on the IDC data is available from the Federal Reserve Board (Byrne, 2015b).

data networking and transmission equipment which supported the IT boom of the 1990s, and to the mobile networking equipment which has been central to more recent IT advances.[37] The Federal Reserve publishes indexes for these products. Recently, in a major step forward, the BLS has adopted a hedonic approach to constructing its price index for smartphone consumption.[38] However, major gaps in our understanding remain. Price-performance trends for satellite equipment and a variety of radio-wave base station equipment are not well understood, due in part to the obscurity of relevant prices within complicated contracts.[39] And, there has been no research on prices for broadcast and studio equipment for radio and television, a major component of communication equipment spending, and an important area of the ongoing transition to solid state electronics from legacy technologies.

- **Special purpose equipment**:[40] In addition to computing and communications equipment, which are designed for general purpose use, the electronics industry produces a host of equipment for more narrow applications. This portion of the electronics industry is almost entirely uncharted measurement territory and accounts for the bulk of the U.S. final electronics manufacturing (Byrne, 2015a).[41] Interestingly, the share of the intermediate inputs used in their manufacture accounted for by electronic components roughly matches the share for the communications equipment industry, suggesting similar underlying downward pressure on their price trends. Yet investment prices for special purpose equipment are largely flat, edging down an average of 0.5 percent per year for 2015-2019 while investment prices for communications equipment fell 7.5 percent. Although these industries differ

[37] See the seminal work on data networking and transmission in Doms (2009), and analysis of prices for the entire scope of communications equipment in Byrne and Corrado (2015).

[38] The BLS index is not published separately, but in communication with the author, analysts have confirmed that the indexes are similar to the results in Aizcorbe, Byrne and Sichel (2020).

[39] Work is underway on satellites at BEA (Highfill and MacDonald, 2022).

[40] "Special purpose equipment" is shorthand for the primary products of NAICS industry 3345, "Navigational, Measuring, Electro-medical, and Control Instruments Manufacturing."

[41] Trajtenberg (1990) examines prices for CT scanners, a lonely exception to this statement.

in noteworthy ways that may affect their output prices, such as market structure and scale economies, the contrast in price declines does suggest more research is merited.

A.3 Emerging Sources and Methods

Price index research has until recently relied primarily on commercially available consultancy data and data collected from product catalogs and company price lists. After many years of torture, those datasets give up fewer and fewer secrets, but new sources and methods offer the prospect of further progress:

- **Point of sale data**: The use of point of sale data, collected by barcode scanners in retail establishments, for example, is hardly new in economics, dating at least back to Guadagni and Little (1983). However, fully exploiting "scanner data" to produce constant-quality price indexes at scale is a work in progress. The "tidal wave of information" identified by Feenstra and Shapiro (2003) as a challenge posed by scanner data is only now becoming manageable after nearly 20 years of further improvement in computing efficiency and development of big data techniques. And, whether cost-benefit analysis supports adopting these data sources is still an open question for statistical agencies (Konny, William and Friedman, 2019). Ehrlich, Haltiwanger, Jarmin, Johnson and Shapiro (2019) demonstrate the feasibility of an array of price index techniques with scanner data, including hedonic indexes feasible without hand curation of the hedonic regression for each product. Further, they exploit current period expenditure weights, product characteristics, and comprehensive (not sampled) coverage of available products.[42] New avenues for price collection via the internet have also supported projects to refine price estimation across a wide range of products, including electronics.[43] Like scanner data, "web scraped" data has the appeal of high-frequency observation, product characteristics information, and extensive product coverage, but lacks weights

[42] Updated results are available in Ehrlich, Haltiwanger, Jarmin, Johnson, Olivares, Pardue, Shapiro and Zhao (2021).

[43] Examples include the Billion Prices Project (http://www.thebillionpricesproject.com) and the Adobe Digital Economy Index (https://www.adobe.com/experience-cloud/digital-insights/digital-economy-index.html).

indicating how often products are sold at the observed prices, if at all. And, though freely available (subject to website license restrictions), web scraped data requires extensive knowledge of the price posting practices of the online source to effectively employ the data, though some platforms provide APIs (application program interfaces). Unfortunately, point of sale data does not have exhaustive coverage for data processing equipment. Data is available for data processing consumer durables as well as high-volume moderately-priced business equipment like PCs, but typically not for high-priced items such as large scale computing equipment and special-purpose electronics.

- **Machine learning**: Machine learning (ML) techniques have recently been applied to uncovering product characteristics latent in unstructured data and to selecting the functional form for hedonic regressions.[44] When performed by the price analyst, model specification—the selection of covariates and the functional form for the hedonic equation—is time-consuming process requiring deep knowledge of the product features, the market, and the dataset used. The algorithmic approach provided by ML offers the prospect of reducing this burden immensely, lowering the cost of developing more accurate price indexes for researchers and statistical agencies and offering the prospect of widespread use of hedonic and other techniques, rather than limited, targeted use for selected problematic products. Bajari, Cen, Chernozhukov, Manukonda, Wang, Huerta, Li, Leng, Monokroussos and Vijaykunar (2021), discern product characteristics in the unstructured text descriptions and images available in listings on Amazon.com using unsupervised ML—without guidance from the analyst. This work opens up the possibility of controlling for product quality for electronics using characteristics not easily articulated and quantified, such as cosmetic and ergonomic design elements. Ehrlich et al. (2019) use supervised learning to group products according to the compact product descriptions available in scanner data which are unintelligible to human readers. Both papers use machine learning for model functional form selection as well. Illustrating the feasibility of ML for statistical agencies, the BLS has recently adopted a ML approach to model selection in their producer price index for MPUs, allowing them to be agnostic about which characteristics to employ as they control for

[44] Athey (2019) provides a description of ML and its recent use in applied economics.

quality change (Sawyer and So, 2018). A key consideration in the adoption of ML approaches, particularly for statistics used in public policy decisions, is their interpretability.[45] Athey (2019) notes that issues of fairness, nondiscrimination, and manipulability of ML models naturally arise. Digital platform companies often store their data in a "data lake" to avoid imposing structure on their ML process, but this approach may make interpretation of the results more difficult, an undesirable outcome for public policy. For example, to the degree that latent relationships suggest revising consumer price measures noticeably lower to account for rising quality in IT goods and services, cost of living adjustments to Social Security benefits will be lower—an outcome that will surely elicit calls for an explanation.

- **Market share information**: An opportunity to structurally identify constant-quality price trends is provided by changes in product market shares under the assumption that these shifts reflect choice behavior in response to changing relative prices (Feenstra, 1994; Redding and Weinstein, 2020). Statistical agencies typically collect market share information independently of price surveys, at a lower frequency, and at a lower level of product granularity. However, when revenue (or units) is collected at the product model level simultaneously with prices, shifting shares provide insight into product valuations. Ehrlich et al. (2019) compare alternative techniques to exploiting this information to both conventional matched-model and hedonic indexes, demonstrating feasibility and identifying challenges posed by this emerging approach. Most prominent among them is how to mitigate the influence of structural assumptions about the demand system on the resulting price indexes.

- **Benchmark test scores**: Most hedonic analysis of prices for data processing equipment has focused on physical characteristics, such as the "clock speed" of MPUs. However, performance on tasks of interest to the user is the ultimate barometer of quality.[46] If a higher clock speed MPU delivers, say, a higher speed of file compression, users will prefer the chip, but the chip is not preferable to the user because of

[45] Lipton (2018) discusses formalization of the "interpretability" concept.

[46] Ohta and Griliches (1976) state succinctly that "ideally, quality adjustments should be based on performance variables, which presumably enter the utility function directly, not physical characteristics."

its clock speed *per se*. If benchmark scores on relevant tasks are available, they are more direct approach to controlling for quality.[47] That said, provided physical features have a strong, stable relationship with performance, they serve as a reasonable proxy measure for quality.[48] Famously, clock speed for high performance MPUs is a counter-example in recent years; formerly a good predictor of performance, advances in clock speed stalled in the early 2000s, yet performance continued to climb (Byrne, Oliner and Sichel, 2018b). Moreover, using benchmarks allows the price analyst to be agnostic about how the equipment delivers performance—that is, which physical features are relevant—while leveraging the expertise of the engineers designing the benchmark tests to represent common uses for the equipment. Examples of electronic products with benchmarks available but no plausible price indexes are graphics processor units (GPUs), now used in a host of computing applications, and industrial robots, a class of special purpose equipment.[49] In short, more attention to leveraging the benchmarking efforts of the engineering community in this area is in order.[50]

- **Input costs**: Under sufficiently competitive conditions, we expect the price of goods to track the weighted prices of the inputs used less any growth in total factor productivity (TFP)—the amount of output yielded by a fixed set of inputs. Prices for software and for research and development in the NIPAs exploit this relationship (Grimm, Moulton and Wasshausen, 2009). In cases where input prices are measured well but output prices are not, this approach is particularly appropriate, though it requires one to assume a growth rate for TFP. For some types of data processing equipment, such an assumption may be well

[47]See the extensive discussion of computer performance and benchmarks in Jorgenson and Wessner (2005), especially Triplett (2005) in that volume.

[48]Chwelos (2003) studied laptop prices and found physical features provided a reasonably proxy for benchmark performance through 2002. Byrne, Oliner and Sichel (2018b) found markedly different results with data from more recent years.

[49]Bi, Miao, Zhang and Zhang (2020) provide an introduction to the efforts of the National Institute for Standards and Technology to develop and promote performance measures for industrial robots.

[50]For example, the Institute of Electrical and Electronics Engineers has a technical committee striving to "achieve better and agreed ideas on agreed ideas on how to define and measure system level characteristics like autonomy, cognition, and intelligence" (https://www.ieee-ras.org/performance-evaluation).

supported. In the electronics industry, a wide array of products are designed and produced—that is, assembled from components—under similar conditions by a small set of contract manufacturing firms. In that context, estimates of TFP growth from products where both inputs *and* outputs are well measured, such as personal computers, may serve as an plausible indicator for TFP growth in the production of the host of electronic devices without plausible output indexes. That is, a reasonable indicator of constant-quality prices for a gaming console or a printer may be the appropriate input cost index for the industry adjusted by the proxy TFP measure from PC production.

Appendix B NAICS Coverage of Digital Platforms

From the outset, NAICS was intended to provide useful detail on the digital economy. To that end, an information sector was identified, defined as "establishments engaged in the following processes: (a) producing and distributing information and cultural products, (b) providing the means to transmit or distribute these products as well as data or communications, and (c) processing data." (Its predecessor, SIC (the Standard Industry Classification System) made no mention of the internet or the worldwide web, for obvious reasons.) At the time, web pages were static, ruling out the possibility of digital platforms with customized recommendations. As database management systems and machine learning advanced, and as the web moved toward accommodating user-generated content (Web 2.0), digital platforms emerged and NAICS treatment of their establishments evolved. The definitions of relevant industries for digital platforms from each vintage of NAICS provided below illustrate this evolution. In addition, NAICS provides cross-references to provide guidance on classifying establishments with a mix of activity. Selected relevant cross-references are included as well.

Datasets employing NAICS, such as the Economic Census, classify establishments according to their "principal product or group of products produced or distributed, or services rendered." The 2022 NAICS manual provides this guidance: "Ideally, the principal good or service should be determined by its relative share of current production costs and capital investment at the establishment. In practice, however, it is often necessary to use other variables such as revenue, shipments, or employment as proxies for measuring significance." Importantly, revenue is frequently used as the practical measure of significance. In light of the fact that many digital platform services are provided for free, it is likely that many digital economy establishments are classified elsewhere.

B.1 1997 NAICS

- **51419 Other Information Services** This industry comprises establishments primarily engaged in providing information services (except news syndicates, libraries, and archives). Included in this industry are Internet service providers, on-line information access services, and telephone-based (i.e., toll call) information services. On-line information services establishments are engaged in the provision of direct access to computer-held information published by others via telecommunications networks. These establishments often provide electronic mail services, bulletin boards, browsers, and search routines.

B.2 2002 NAICS

- **516110 Internet Publishing and Broadcasting** This industry comprises establishments engaged in publishing and/or broadcasting content on the Internet exclusively. These establishments do not provide traditional (non-Internet) versions of the content that they publish or broadcast. Establishments in this industry provide textual, audio, and/or video content of general or specific interest on the Internet.

  Cross-References. Establishments primarily engaged in–

  - Providing both Internet publishing and other print or electronic (e.g., CD-ROM, diskette) editions in the same establishment or using proprietary networks to distribute content–are classified in Subsector 511, Publishing Industries (except Internet) based on the materials produced;
  - Operating web search portals–are classified in U.S. Industry 518112, Web Search Portals;
  - Providing streaming services on content owned by others–are classified in Industry 518210, Data Processing, Hosting, and Related

Services;

  – Wholesaling goods on the Internet–are classified in Sector 42, Wholesale Trade;

  – Retailing goods on the Internet–are classified in Sector 44-45, Retail Trade; and

  – Operating stock brokerages, travel reservation systems, purchasing services, and similar activities using the Internet rather than traditional methods–are classified with the more traditional establishments providing these services.

  – Providing Internet access, known as Internet Service Providers–are classified in U.S. Industry 518111, Internet Service Providers

- **518112 Web Search Portals** This U.S. industry comprises establishments known as web search portals. Establishments in this industry operate web sites that use a search engine to generate and maintain extensive databases of Internet addresses and content in an easily searchable format. Web search portals often provide additional Internet services, such as e-mail, connections to other web sites, auctions, news, and other limited content, and serve as a home base for Internet users.

  The cross-references listed above for NAICS 516110 apply to this industry as well.

- **518210 Data Processing, Hosting, and Related Services** This industry comprises establishments primarily engaged in providing infrastructure for hosting or data processing services. These establishments may provide specialized hosting activities, such as web hosting, streaming services or application hosting, provide application service provisioning, or may provide general time-share mainframe facilities to clients. Data processing establishments provide complete processing and specialized reports from data supplied by clients or provide automated data processing and data entry services.

  Cross-References. Establishments primarily engaged in–

  – Providing Internet access services in combination with web hosting–are classified in U.S. Industry 518111, Internet Service Providers

B.3 2007 NAICS

- **518210 Data Processing, Hosting, and Related Services**

  The definition of this industry is unchanged from NAICS 2002.

- **519130 Internet Publishing and Broadcasting and Web Search Portals** This industry comprises establishments primarily engaged in 1) publishing and/or broadcasting content on the Internet exclusively or 2) operating Web sites that use a search engine to generate and maintain extensive databases of Internet addresses and content in an easily searchable format (and known as Web search portals). The publishing and broadcasting establishments in this industry do not provide traditional (non-Internet) versions of the content that they publish or broadcast. They provide textual, audio, and/or video content of general or specific interest on the Internet exclusively. Establishments known as Web search portals often provide additional Internet services, such as e-mail, connections to other web sites, auctions, news, and other limited content, and serve as a home base for Internet users.

B.4 2012 NAICS

- **518210 Data Processing, Hosting, and Related Services**

  The definition of this industry is unchanged from NAICS 2002.

- **519130 Internet Publishing and Broadcasting and Web Search Portals**

  The definition of this industry is unchanged from NAICS 2007.

B.5 2017 NAICS

- **518210 Data Processing, Hosting, and Related Services**

  The definition of this industry is unchanged from NAICS 2002.

- **519130 Internet Publishing and Broadcasting and Web Search Portals**

The definition of this industry is unchanged from NAICS 2007.

B.6 2022 NAICS

- **516210 Media Streaming Distribution Services, Social Networks, and Other Media Networks and Content Providers** This industry comprises establishments primarily providing media streaming distribution services, operating social network sites, operating media broadcasting and cable television networks, and supplying information, such as news reports, articles, pictures, and features, to the news media. These establishments distribute textual, audio, and/or video content of general or specific interest.

- **519290 Web Search Portals and All Other Information Services** This industry comprises establishments primarily engaged in operating Web sites that use a search engine to generate and maintain extensive databases of Internet addresses and content in an easily searchable format (and known as Web search portals) or providing other information services not elsewhere classified. Establishments known as Web search portals often provide additional Internet services, such as email, connections to other Web sites, auctions, news, and other limited content.