Valuing the U.S. Data Economy Using Machine Learning and Online Job Postings*

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Abstract

With the recent proliferation of data collection and uses in the digital economy, the understanding and statistical treatment of data stocks and flows is of interest among compilers and users of national economic accounts. In this paper, we 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. Our method augments the traditional sum-of-costs methodology for measuring other own-account intellectual property products in national economic accounts by proxying occupation-level time-use factors using a machine learning model and the text of online job advertisements (Blackburn 2021). In our experimental estimates, we find 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. In addition to annual current-dollar investment, we present historical-cost net stocks, real growth rates, and effects on value-added by industrial sector.

Keywords: Data Assets, System of National Accounts, Digital Economy, Intangible Capital, Measurement

JEL Codes: E22, O3, O51

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1 Introduction

With the recent proliferation of data collection and uses in the digital economy, the understanding and statistical treatment of data stocks and flows is of interest among compilers and users of national economic accounts. During the last revision of the *System of National Accounts* (*SNA*) (United Nations 2010), which is the international standard for national economic accounts, the treatment of data stocks and flows was a topic of discourse among statistical agencies and international organizations, who ultimately settled on the treatment of *databases* as a subcategory of software in capital formation (Ahmad 2004; Ahmad 2005). Current global efforts for the next revision of the *SNA*, expected to be published in 2025, have a renewed focus on the valuation and recording of the information content of databases – i.e., the embedded *data* – in response to the presumed rapid increase in data stocks and flows over the last decade and longer.

The value of data is implied in the profits and market values of some firms. In 2020, two of the largest global data firms – Alphabet Inc. (Google) and Meta Platforms Inc. (Facebook) – had a combined net income before tax of $81.3 billion, which amounted to 3.7 percent of U.S. corporate profits before tax. In November 2021, the combined market capitalization of the two firms was $2.9 trillion, which amounted to 7.5 percent of the market capitalization of all S&P 500 firms.[1] While the value of data may be implied in these measures, data stocks and flows are not visible in national economic accounts under the current *SNA* treatment. Moreover, understanding and measuring the value of data presents challenges to economic statisticians.

In this paper, we 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. To estimate production costs, we apply a markup to an estimate of the wage bill for data-related

[1]Net income before tax comes from each firm's 10-K filings with the U.S. Securities and Exchange Commission for year-end December 31, 2020. Corporate profits come from BEA's National Income and Product Accounts table 6.17D. Market capitalizations come from YCHARTS (GOOG, FB) as of November 19, 2021.

activities, which is consistent with the Bureau of Economic Analysis (BEA) methodology for own-account software. Our method 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 (Blackburn 2021).

The occupation-level time-use factors can be decomposed into two components: 1) the fraction of jobs in an occupation engaged in qualifying activities based on data-relevant skills revealed in the job advertisement and 2) the average share of time allocated to the data-relevant activities. Using online job advertisements from Burning Glass Technologies (BGT), skills in the BGT taxonomy that are relevant to data-related activities are identified, including data entry, storage, analysis, and management. The fraction of jobs in an occupation engaged in qualifying activities is given by the fraction of BGT job advertisements that contain at least one of the data-relevant skills. The average time allocation is based on the distance of an occupation to known data-intensive occupations that serve as "landmark" occupations (e.g., data entry keyers or statisticians). A doc2vec model is then trained on the job advertisement text for each occupation to obtain a numerical representation of what the occupation-level job postings convey. Using the numerical representation, occupation-level pair-wise distances are obtained to measure how "close" or similar an occupation is to the landmark occupations. The product of the similarity to a landmark occupation and the ratio of job openings with identified data-relevant skills serves as the proxy for the occupation-level time-use factor. We then apply the time-use factors to the product of average annual wages and annual number of employees by occupation at the 3-digit North American Industry Classification System (NAICS) level available from the U.S. Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) to calculate the wage bill (i.e., wages and salaries, excluding employee benefits) for data-related activities.

The main challenges for measurement of own-account data stocks and flows that we address in the paper are similar to challenges imposed by other own-account IPPs that are

already included in capital formation in the *SNA* and the U.S. National Income and Product Accounts (NIPAs). First, the scope of capital formation is not yet well-defined for own-account data. Second, own-account data and other own-account IPPs are at risk of multiple counting from sources such as overlap among categories of IPPs and non-rival use of data. A third challenge is what proportions of the sum-of-costs should be accounted for by labor costs, capital costs, and intermediate consumption in light of the role that capital services play in the collection, storage, analysis, and management of data. Finally, own-account data are not transacted in active markets, which means there are no observed transactions that are useful for measuring prices and depreciation. We discuss each of these challenges and our approach to addressing them in section 4 of the paper.

Our experimental results 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, which yields an average annual growth rate of 4.2 percent. Cumulative current-dollar investment for the period 2002–2021 was $2.6 trillion. Annual current-dollar investment in own-account data for the period averaged 1.0 percent as a share of business sector value-added, 5.0 percent as a share of investment in private fixed assets, and 20.2 percent as a share of investment in IPPs. Likewise, the historical-cost net stock of data assets grew from $205 billion in 2002 to $421 billion in 2021, which yields an average annual growth rate of 3.8 percent. Using an experimental price index that we developed for data, the average annual growth rate in real data investment over the period was 7.5 percent, which yields an average annual increase in real business sector value-added growth of 4 basis points and an increase in growth in real investment in IPPs of 31 basis points. In contrast, growth in real data investment is lower than growth in real investment in software, which yields a decline in average annual growth of real investment in software of 26 basis points. For NAICS sectors, the largest dollar investments were made in Professional, Scientific, and Technical (PST) Services (NAICS 54), Manufacturing (NAICS 31-33), and Finance and Insurance (NAICS 52). The largest increases in average real value-added growth by NAICS sector shows up for

Management of Companies (NAICS 55) and PST Services (NAICS 54).

The next section summarizes the *SNA* background on the treatment of own-account data stocks and flows and related literature. Section 3 provides details on our measurement, including source data and methodologies. Section 4 identifies challenges associated with measurement of own-account IPPs and how we address those challenges for own-account data. Section 5 reports our core experimental results and some additional experimental results of interest. Section 6 concludes.

2 National Accounts Background and Related Literature

2.1 *System of National Accounts*

The 1993 version of the *SNA* includes only a brief paragraph on the inclusion of "large databases that the enterprise expects to use in production over a period of time of more than one year" as part of the computer software category of capital formation (United Nations 1993, paragraph 10.93). There is no mention of embedded information content (i.e., data) in *SNA 1993*. Leading up to the 2008 version of the *SNA*, an *SNA* group of statistical agencies and international organizations considered the inclusion of embedded data in capital formation. To guide the discussions, Ahmad (2004) outlined two components of databases – supporting software and data stored in the database – and summarized practical challenges that countries encounter while trying to implement the vague *SNA 1993* recommendation. In light of the challenges, Ahmad (2005) described two definitions for databases considered by the *SNA* group. One definition included the value of the information content to be stored in databases as long as the information had a useful life of more than one year, and one definition did not include the value of the information content. The group recommended that the latter definition is preferable because the former definition would "open the door

to the capitalization of knowledge" (Ahmad 2005, p. 2). Based on the summary outlined in Ahmad (2005), the group primarily considered databases maintained by statistical agencies.

The recommendation that was ultimately written into *SNA 2008* includes databases and computer software as separate categories of intellectual property products in capital formation (United Nations 2010, paragraphs 10.109–10.114). If a database is developed for own use, *SNA 2008* recommends a sum-of-costs approach to value the database. The sum-of-costs includes the cost of preparing data in a format that conforms to the database but excludes the cost of acquiring or producing the data. In addition, the sum-of-costs excludes the value of the database management system (DBMS), which is included instead with computer software. If a database is developed for sale or for license, the value should be determined by the market price, which includes the value of the information content. Thus, *SNA 2008* recommends an inconsistent treatment for data in capital formation depending whether a database is developed for own use or for sale or license. In addition, the value of data acquired or produced for inclusion in databases is not to be treated as intermediate consumption in the sum-of-costs approach for own-account databases, which is inconsistent with the inclusion of intermediate consumption in the usual sum-of-costs measurement. The overall conclusion drawn by the *SNA* group was that if data is an asset, it is a non-produced asset whose value should be limited in national accounts to measures of purchased goodwill. Thus, there should be no value of data reflected in production measures.

2.2 U.S. National Accounts

The U.S. national accounts are consistent with the *SNA* recommendations on intellectual property products, including computer software (U.S. Bureau of Economic Analysis 2020). Similar to general practice in other countries, the U.S. accounts do not include a separation between software and databases (i.e., the software that houses data) in published capital stock and flow measures. The value of any data included in purchased software is included in measures of investment and capital stock. The value of any data in own-account software

is excluded from measures of investment and capital stock.

BEA estimates three categories of software: 1) prepackaged, 2) custom, and 3) own-account. Benchmark estimates of prepackaged and custom software are determined using a commodity flow method based on receipts reported in the U.S. Economic Census for Software Publishers (NAICS 5112), Data Processing and Hosting (NAICS 518), and Computer Systems Design (NAICS 5415). For non-benchmark years, estimates are based on receipts reported in the Census Bureau's Service Annual Survey. Benchmark estimates of own-account software are determined using a sum-of-costs methodology based on wage data in the BLS OEWS for four occupations - Computer Programmers, Computer Systems Analysts, Software Developers, and Software Quality Assurance Analysts - and based on the Economic Census. For non-benchmark years, estimates are primarily based on the OEWS data. In addition to labor costs and intermediate consumption, own-account software includes a cost for capital services (Chute et al. 2018).

2.3 Related Literature

Two strands of literature provide additional context for this paper. The first is literature on the value of data, which not only suggests that data has value but also suggests that the value of data may, at least in part, be a result of a production process rather than non-produced, which is the current perspective in national economic accounts. The second is emerging literature from statistical agencies, international organizations, and other sources that is beginning to recognize the likelihood that some data are produced assets and to generate renewed focus for recording and valuing data stocks and flows.

2.3.1 Value of Data

Varian (2018) describes a data pyramid that is a variation of the data-information-knowledge-wisdom (DIKW) hierarchy introduced by Ackoff (1989) and subsequently used in information science and economics (Rowley 2007; Boisot and Canals 2004). The data pyramid is used to

illustrate the relationships among data that is stored as bits, information that is stored in documents, and knowledge that is stored in the human mind (Mokyr 2013). Related to the data pyramid is the data value chain presented in OECD (2013) and subsequently expanded in Moro Visconti et al. (2017). The data value chain illustrates a production process for data from an unstructured form that has very little value to a structured form that can be leveraged in a business model or other usage (Bakhshi et al. 2014). The stages of the chain include collection, storage, processing, distribution, and usage. The Moro Visconti et al. (2017) version of the data value chain focuses on business users at the last stage of the chain with the monetization of data via a business model, which may be data-dependent or data-neutral. Data-dependent business models, such as online platforms, rely heavily on data for sources of revenue and profits (Li et al. 2019; Nguyen and Paczos 2020). Data-neutral firms do not depend on data for revenue but can still realize benefits from data that help improve existing products or offer new products. The OECD (2013) version of the data value chain includes business users and also includes government, non-profit, and household users.

Hughes-Cromwick and Coronado (2019) outline the value of U.S. government data to business decision-making. Likewise, the value of household data is evident in literature on the economics of personal privacy, which has re-emerged as an area of interest as summarized in Acquisti et al. (2016).

Farboodi and Veldkamp (2021) construct a growth model of the data economy in which data is an information asset that contributes to growth by reducing uncertainty and helping firms choose better production techniques via forecasts. The model demonstrates short-run increasing returns due to a feedback loop within the firms. However, long-run diminishing returns result in the absence of traditional technological progress in the Solow (1956) growth model because better forecasts are not a tool that can logically sustain long-run growth. In contrast to Farboodi and Veldkamp (2021), Jones and Tonetti (2020) model data contributing directly to productivity and generating long-run growth.

2.3.2 Recording and Valuing Data Stocks and Flows

Under the second strand of literature, statistical agencies and international organizations are renewing efforts to introduce guidelines for recording and valuing data as a produced asset in national economic accounts. Ahmad and van de Ven (2018) and Reinsdorf and Ribarsky (2020) provide background on the historical treatment of data stocks and flows and offer preliminary thoughts on moving forward with changes to the *SNA*. Rassier et al. (2019) also summarize considerations for treatment of data stocks and flows and present cursory estimates of data-related flows based on official statistical sources for the U.S. economy. Statistics Canada (2019b) carefully defines and categorizes data, databases, and data science and presents experimental estimates for each category using a sum-of-costs measurement methodology for the Canadian economy. The Australian Bureau of Statistics and the Netherlands Central Bureau of Statistics have compiled measures of data stocks and flows based on the Canadian methodology. Each of these previous efforts have resulted in preliminary guidance that is currently being considered by the *SNA* community (United Nations Inter-Secretariat Working Group on National Accounts 2022).

Goodridge et al. (2021) are the first to provide a harmonized set of cross-country estimates for data assets in European Union countries and then estimate the contribution of data capital deepening to growth in productivity. They find that about 43 percent of employment engaged in capital formation of software and data is unaccounted for in measured own-account software and databases, and the missing piece of capital formation is growing faster than the measured piece. Goodridge et al. (2021) also provide a summary of previous economic literature on information and knowledge.

3 Data and Methods

The *SNA* recommendation for valuing IPPs that lack an observable market transaction is a cost-based approach including labor costs, capital costs, and intermediate consumption.

For market producers, capital costs include a net return to fixed assets (or "normal profit") in addition to consumption of fixed capital. Our strategy builds on BEA's sum-of-costs methodology for own-account software. Estimates of aggregate production costs for data-related output have the general form

$$C_{i,t} = \alpha \sum \tau_{\omega} W_{\omega,i,t} H_{\omega,i,t} \tag{1}$$

where for each occupation ω, industry i, and year t, we calculate the wage bill by multiplying the annual number of employees ($H_{\omega,i,t}$) by the average annual wage ($W_{\omega,i,t}$) and an occupation-specific time-use factor (τ_{ω}) that reflects the time-effort that the occupation allocates to data-related activities. The parameter α is a markup that reflects employee benefits (not included in the wage bill), capital costs, and intermediate consumption, which yields the full production costs. The rest of this section discusses our estimation of each of the elements in equation 1.

3.1 Employment and Wage Data

The U.S. Bureau of Labor Statistics (BLS) has 12 survey programs that provide information on pay and benefits. We prioritize having wage data at an occupational level specific enough to capture the activities of interest.[2] The BLS Occupational Employment and Wage Statistics (OEWS) program produces employment and wage estimates annually for around 800 occupations and is well-suited for our purpose. In addition, the historical data temporal coverage dates back to the early 2000s, allowing us to generate a longer time series. Occupational data collected by the U.S. federal statistical system is generally collected, calculated, and disseminated based on the Standard Occupational Classification (SOC) system. Employees are assigned to an occupation based on the work they perform and not on their education or training. The OEWS data are an SOC-based occupational system that uses

[2] `https://beta.bls.gov/comparison-matrix`

SOC codes to assign occupations at levels for which the data are published. Some SOC codes are aggregated into a single OEWS occupational code for reporting purposes. The OEWS system allows the data to be linked to other systems such as the U.S. Department of Labor (DOL) Occupational Information Network (O*NET) (Hopson 2021). The OEWS program reports data using the North American Industry Classification System (NAICS). We use estimates at the NAICS 3-digit subsector levels that are representative of privately-owned business establishments, which excludes government and nonprofit institutions serving households (NPISH).[3]

To generate data-related employment and wage estimates for 2002–2021, we use model-based estimates (Dey et al. 2019) for 2015–2020 and official estimates for the period 2002–2014 and 2021 (U.S. Bureau of Labor Statistics 2021). We use estimates of the average annual wage and annual number of employees for privately-owned establishments at the NAICS 3-digit level. The wage series use several versions of the underlying occupational and industry systems across time. In order to obtain a consistent time series, we use the OES 2021 hybrid structure crosswalk and rely on the OES 2010–2011 classification crosswalk to account for the temporary codes in those two years. For example, if multiple occupations are aggregated in the latest taxonomy (OEWS 2021), the estimated average annual wage is an average of available wage data weighted by the employment estimates for the corresponding occupations. In cases when an occupation is attributed to multiple 2021 codes, which may occur due to special hybrid-code estimates, those are equally distributed among the corresponding 2021 codes. The resulting series provide us the employment and wage numbers by occupation, year, and industry.

[3]The sectors and subsectors identified as NPISH include Educational Services (NAICS 61), Health Care and Social Assistance (NAICS 62), Arts, Entertainment and Recreation (NAICS 71), and Religious, Grant-making, Civic, Professional, and Similar Organizations (NAICS 813).

3.2 Time-Use Factors

Time-use factors are important to the sum-of-costs methodology as they provide measures of time-effort allocated to the activities of interest such as data-related activities. Time-use factors have been used to examine quality of service, job satisfaction, and other outcomes in various domains such as education, health, and security. For example, the OECD Teaching and Learning International Survey (TALIS) collects data on the time-use allocation of teachers among categories: (1) Administrative and leadership tasks and meetings, (2) Curriculum and teaching-related tasks and meetings, (3) Student interactions, (4) Parent or guardian interactions, and (5) Interactions with local and regional community, business and industry. In the area of health, studies have collected information on the share of time physicians spend on direct care with patients or administrative work (Woolhandler and Himmelstein 2014). While most data on time-use allocations is collected in surveys, other methods include direct observation of the work performed such as rides with police officers (Parks et al. 1999). For data as an asset, we estimate time-use factors using a methodology developed in Blackburn (2021) for data-relevant skills, which are reflected in activities including entry, storage, analysis, and management of data. Examples of specific activities include data cleaning, data wrangling, data manipulation, and data science. Following Blackburn (2021), the time-use factor τ can be decomposed as follows

$$\tau_\omega = \frac{l_\omega}{L_\omega} s^*_\omega = \rho_\omega s^*_\omega \tag{2}$$

where the time-use factor for occupation ω is the product of the fraction of employees that engage in activities of interest (ρ_ω) and an estimate of how much time the occupation allocates to the activities (s^*_ω). Without time-use factors, the sum-of-costs methodology relies on identifying specific occupations assumed to best embody the activities of interest.

3.2.1 Online Job Advertisements

The method uses online job advertisement data from Burning Glass Technologies (BGT) to estimate time-use factors for a broad range of occupations.[4] The data not only contain the job advertisement text but also enhancements, including deduplication, identified skills, degree requirements, location, and information on the employer (e.g., industry). BGT also uses their own-developed occupational auto-coders to identify the occupation of the job advertisement.[5]

Lancaster et al. (2021) look at the data quality, suitability, and representativeness of BGT job advertisement data for research purposes. The study confirms several findings in the literature such as the over-representation of certain occupation groups in the BGT job advertisement data. One aspect of the BGT data that distinguishes them from other alternatives is the focus on skills rather than occupations as the main unit of analysis for understanding the job market (Burning Glass Technologies 2019). The BGT skills taxonomy includes over 17,000 skills as well as various skill properties such as whether a skill refers to data or software (or both).

The strategy uses the BGT job advertisement data to estimate equation 2. The first component refers to the fraction of employees in an occupation who engage in data-related activities. The concept is operationalized with the following definition:

$$\hat{\rho_\omega} = \frac{\sum_{j=1}^{L_\omega} \mathbb{1}\left(\hat{y_j}\right)}{L_\omega} \tag{3}$$

where $\mathbb{1}\left(\hat{y_j}\right)$ denotes $\exists\ s : s \in S$ meaning s is a subset of skills identified for job advertisement y_j, and S is the set of skills identified as data relevant. In other words, a ratio is computed as the fraction of job advertisements with at least one of the data-relevant skills out of all job advertisements (L_ω) for each occupation. Blackburn (2021) manually identified 203 BGT

[4]Online job advertisements have been used in applications related to labor, education, and credential research. Examples of online job advertisement providers include Burning Glass Technologies, Indeed, and the National Labor Exchange (NLx) Research Hub. These providers collect job postings in "real-time" from various websites.

[5]The NLx Research Hub uses the O*NET SOC Code AutoCoder™ (`https://www.onetsocautocoder.com`).

Table 1: BGT skills identified as data relevant

3D Seismic Data	Data Dictionary System
Accenture Data Governance Framework	Data Documentation
Advanced Data Entry	Data Encryption
Assessment Data	Data Engineering
Big Data	Data Entry
Big Data Analytics	Data Entry Prioritization
Billing Data Analysis	Data Evaluation
Biological Database Search	Data Exploitation
Business Intelligence Data Modeling	DFHSM
Cascading Big Data Applications	Data Flow Diagrams (DFDs)
Climate Data Analysis	Data Governance
Clinical Data Abstracting	Data Integration
Clinical Data Analysis	Data Integrity
Clinical Data Exchange	Data Lakes / Reservoirs
CDISC	Data Loss Prevention
Clinical Data Management	Data Management
Clinical Data Review	Data Management Platform (DMP)
Clinical Data Understanding	Data Manipulation
Clinical Database Development	Data Mapping
Clinical Research Data Accuracy and Integrity	Data Migration
Cloud Security Data Protection And Privacy	Data Mining
Columnar Databases	Data Mining Industry Knowledge
Conceptual Data Models	Data Modeling
Customer Data Integration	Data Modeling Star / Snowflake Schema
Customer Service Database	Data Multiplex System (DMS)
Data Acquisition	Data Munging
Data Acquisition Systems	Data Operations
Data Analysis	Data Platform as a Service
Data and Safety Monitoring Board	Data Pre-Processing
Data Architecture	Data Privacy
Data Archiving	Data Protection Industry Knowledge
Data Buffers	Data Protection Planning
Data Capture	Data Protection Strategy
Data Center Hardware	Data Quality
Data Cleaning	Data Quality Assessment
Data Collection	Data Reports
Data Communications	Data Science
Data compression	Data Security
Data Conversion	Data Security Classification

Note: Top 80 skills by frequency out of 203 data relevant skills identified manually (Blackburn 2021).

Table 2: Landmark occupations

O*NET SOC 2010	Description	Time-use factor
43-9021.00	Data Entry Keyers	0.94
15-1111.00	Computer and Information Research Scientists	0.77
15-1141.00	Database Administrators	0.75
15-1199.06	Database Architects	0.72
19-1029.01	Bioinformatics Scientists	0.68
19-4061.00	Social Science Research Assistants	0.67
15-2041.00	Statisticians	0.66
15-1199.07	Data Warehousing Specialists	0.63
15-2041.01	Biostatisticians	0.63
15-1199.08	Business Intelligence Analysts	0.61
53-7073.00	Wellhead Pumpers	0.60
19-3022.00	Survey Researchers	0.59
43-9111.01	Bioinformatics Technicians	0.58
43-9111.00	Statistical Assistants	0.54
29-2092.00	Hearing Aid Specialists	0.54
15-2041.02	Clinical Data Managers	0.54
43-3021.01	Statement Clerks	0.50

Note: For landmark occupations, the similarity to the nearest landmark is one, and thus the time-use factor $\hat{\tau}_\omega$ is the same as $\hat{\rho}_\omega$.

skills that are data relevant, which excludes any skill deemed a software skill as a way to minimize potential overlap with capital formation in software. The top 80 data-relevant skills by frequency are presented in table 1.

A two-step approach is used to estimate (s^*_ω). The first step identifies the occupations with the highest rate of employees engaged in data-related activities (ρ_ω) based on the BGT skills. Occupations with a ρ_ω of at least 0.50 are denoted "landmark" occupations and assigned full time-effort. Table 2 shows the 17 occupations determined to be landmark occupations. Many of the occupations are obvious landmark candidates such as *data entry keyers* and various research and analyst occupations. Some of the occupations are less obvious as landmarks. For example, *wellhead pumpers* may not be an occupation immediately associated with data, but their job activities rely on monitoring and assessing data in order to act on that information promptly. For non-landmark occupations, s^*_ω is estimated as the cosine similarity to the

closest landmark occupation. Mathematically,

$$\hat{s^*_\omega} = \max_{w \in \mathbb{M}} \left\{ \frac{\mathbf{A}_\omega \cdot \mathbf{A}_w}{\|\mathbf{A}_\omega\| \|\mathbf{A}_w\|} \right\} \tag{4}$$

where $\mathbb{M}$ is the set of landmark occupations, A_ω (i.e., omega) is a numerical representation of occupation ω, and A_w (i.e., double-u) is the mathematical representation of occupation w (i.e., one of the landmark occupations). The effective time-use factor then becomes

$$\hat{\tau_\omega} = \hat{\rho_\omega} \hat{s^*_\omega} = \frac{\sum_{j=1}^{L_\omega} \mathbb{1}\left(\hat{y_j}\right)}{L_\omega} \max_{w \in \mathbb{M}} \left\{ \frac{\hat{\mathbf{A}}_\omega \cdot \hat{\mathbf{A}}_w}{\|\hat{\mathbf{A}}_\omega\| \|\hat{\mathbf{A}}_w\|} \right\}. \tag{5}$$

The estimate for the full production costs of data-related activities for a given industry i at time t is then as follows:

$$\hat{C}_{i,t} = \alpha \sum_{\omega \in \Omega} \left[\frac{\sum_{j=1}^{L_\omega} \mathbb{1}\left(\hat{y_j}\right)}{L_\omega} \left(\max_{w \in \mathbb{M}} \left\{ \frac{\hat{\mathbf{A}}_\omega \cdot \hat{\mathbf{A}}_w}{\|\hat{\mathbf{A}}_\omega\| \|\hat{\mathbf{A}}_w\|} \right\} \right) \hat{W}_{\omega,i,t} \hat{H}_{\omega,i,t} \right]. \tag{6}$$

3.2.2 Sample Design and Description

The BGT data enable observation of over 239 million job advertisements in the United States for 2010–2019. The data include over a thousand O*NET SOC 2010 occupations. The data are used to train an auto-coder model for O*NET SOC 2010 using job text to obtain the numerical representation for each occupation such that we can compute pairwise similarity between occupations. The sample design uses the occupation distribution across NAICS 3-digit subsectors based on the annual number of employees in privately-owned establishments from OEWS for 2015–2020. If observations available at the occupation-industry level are below the target (1,500 × percentage of occupations in a NAICS 3-digit subsector), all observations are included. Otherwise, we sample from the valid observations a targeted sample of 1,500 observations equally distributed based on the sequential order of the job posting dates. We only include occupations for which at least 100 job ads are available, meaning there is complete information for the job text, job posting date (ISO

8601), O*NET SOC 2010, and NAICS subsector. The sample design aims to be representative of the business sector in terms of the occupation-industry interactions and composition as well as temporal changes, while also maintaining desirable properties for modeling, such as avoiding extreme unbalanced classes or making inferences based on limited data. Our goal is different from traditional auto-coders, which may emphasize some metric like accuracy and may prefer to focus on having better performance for frequent occupations over having acceptable performance for less frequent occupations.

Considering the observations with complete information (O*NET SOC 2010 and NAICS 3-digit codes are not always available), we sample occupations for which at least 100 observations are available and limit the observations included per occupation to around 1,500. We also exclude military occupations (SOC major group 55) and those that are exclusive to the public sector like legislators and postal service employees. The sample includes 959 O*NET SOC 2010 occupational codes that have between 101 and 1,548 observations.

The final sample comprises 1.12 million observations for which we recover the job advertisement text as well as the skills for each of the job advertisements. We split the dataset by applying a clustered sampling design based on occupation-industry subsector with 90 percent of the sample being used as the training set and 10 percent as the test set.

3.2.3 Machine Learning Model

The modeling approach uses the doc2vec (Le and Mikolov 2014) implementation in gensim v4.0.1 (Řehůřek and Sojka 2010) for Python (van Rossum and Drake 2009) v3.8.5. The modeling technique uses paragraph vectors to capture the semantics of documents as an alternative to "bag-of-words" or "bag-of-n-grams" representations. In our case, each job advertisement is represented not just by applying a tokenization to the text but by also including indicators for each job advertisement. After training the model, each occupation is represented by a multidimensional numerical abstraction. Once the model has been fitted, we extract the features that are a 1,000-dimensional numerical representation of each

O*NET SOC 2010 code. The pair-wise cosine distance is then computed to obtain the occupation similarity matrix. The similarity matrix allows us to find the most similar landmark occupation.[6]

3.2.4 Validation

Model Validation. Occupation auto-coders are automated models that can predict occupation codes based on inputs such as job advertisements and job titles. One common autocoder regarded as a gold standard is the O*NET-SOC AutoCoder™ developed by R.M. Wilson Consulting, Inc. for the U.S. Department of Labor. There are various ways to evaluate the performance of a multi-class classifier. For example, the classifier accuracy claims for the O*NET-SOC AutoCoder™ are stated based on the inputs, whether it operates on a job advertisement and job title or on just a job title. For job titles and job advertisement text, the model accuracy for predicting O*NET SOC 2021 codes is 85 percent based on their internal test results. Since the model is using just the unstructured job advertisement text, we expect the performance to be lower than the gold standard using additional information. Another consideration is that the labeled data are also based on the BGT auto-coder for O*NET SOC 2010 codes which in turn contains errors from the BGT auto-coder. Given the licensing terms and industry practices, properly assessing the performance of these tools is difficult. For example, a measure of accuracy can be significantly driven by unbalanced classes. Performing well for common occupations in a sample will result in better accuracy even if the performance for many occupations is not as good if those occupations are less common. For the purpose of obtaining a good numerical representation for each occupation, it is more valuable to have good performance for many occupations rather than great performance for a select few. One metric we compute is the unweighted average F1 score on our test set (out-of-sample) of around 120,000 observations for which the model predictions yield an estimate of 0.5 on a 959-dimensional classification problem.

[6]The cosine similarity can take values in the $[-1, 1]$ interval, but in practice yields cosine distances in the $[0, 1]$ interval avoiding the need for other transformations such as angular similarity.

Validation of Landmark Occupations. An alternative strategy for obtaining representative occupations and similarities between occupations is to use the O*NET program. The O*NET tasks file provides estimates of how frequently certain occupations perform job work activities. For example, for the occupation *data entry keyers* (43–9021.00) in the O*NET v26 data, there is a task relevant to data-related activities: "Compile, sort, and verify the accuracy of data before it is entered". For this occupational task, the O*NET data provide a breakdown of how frequently the task is performed: *Yearly or less* (1.49), *More than yearly* (0), *More than monthly* (2.67), *More than weekly* (41.69), *Daily* (18.6), *Several times daily* (18.6), *Hourly or more* (35.54). Each task can then be assigned an indicator of whether it is considered data-relevant or not and estimate a time-use factor for each occupation. Some of the heuristics we employ include assigning the frequency for each task per occupation to the category with the highest value (daily, several times daily, or hourly). At each of the different frequency categories, we compute the fraction of tasks deemed data-relevant. We then collapse the ratios assigning relative values of 10 percent, 20 percent, and 70 percent to daily, several times daily, and hourly, respectively. This back-of-the-envelope heuristic is used as an additional check on our rankings. Martin and Monahan (2022a) presents an alternative methodology to work with O*NET data to obtain time-use factors for green jobs (Martin and Monahan 2022b). To assess whether the landmark occupations are reasonable, we compute Spearman's rank correlation coefficient and obtain a value of around 0.22. The correlation coefficient reveals a negligible correlation, but the machine learning model seems to provide more reasonable rankings than the O*NET-based model.

Time Use Temporal Variation. The estimation of time-use factors used online job advertisements for the period 2010–2019. The estimates are applied to the full series from 2002 to 2021. This approach assumes a representative time-use factor for the full period and restricts potentially significant dynamics such as time-use factor trends both at intensive or extensive margins. For example, more occupations taking on work activities related to the formation of data assets or occupations increasing their time-effort allocation to those

tasks. There are generally limitations with job advertisement data available for pre-2010. An additional challenge to estimating time-variant time-use factors is the low number of advertisements for various occupations that are not highly represented in job advertisement data. Relaxing the time-invariant assumption and assessing appropriate temporal periods could be a beneficial extensions to this work.

Suitability of Job Advertisements. There are two potential issues related to the suitability of the BGT job advertisement data for our methodology and estimates. The first potential issue refers to the results being highly dependent on the BGT process to compile their job ads data. We examined the variability of replicating the time-use factors using a different job ads data set, namely the National Labor Exchange (NLx) Research Hub. We compared only the pair-wise similarity between occupations as the NLx data did not include the "skills taxonomy". The differences were marked but could potentially be caused by how we generated the samples for training the autocoder. The NLx data did not provide the industry classifications for the job postings, which did not allow us to generate a sample representative of the occupation distribution among sectors.

The second potential issue related to job advertisement suitability is the assumption that job advertisements, which are a prospective employer-provided description of expectations, accurately reflect the current functions of the workforce. To assess this assumption, we are currently exploring the American Community Survey (ACS) public use file of occupation and industry write-ins (2019). The public use file includes the raw write-in responses used to assign occupations to respondents as well as their employer's industry classification. These responses are brief summaries of their main job responsibilities/work activities from current employees. The files also include the assigned occupation and industry coding based on the responses.

3.2.5 Mapping Occupational Codes

Using equation 5, we obtain O*NET SOC 2010 level estimates for the time-use factors. However, employment and wage data are collected and prepared with OEWS Employment Projections (EP) 2021 codes. We use the crosswalk files to map the O*NET SOC 2010 codes to the SOC 2010 codes and then to OEWS 2021 codes (see subsection 3.1 for additional information on the process and data files). If multiple occupations are mapped to a single OEWS-EP 2021 code, the time-use factor for that occupation is the mean value for all mapped occupations. We then obtain time-use factor estimates for 736 OEWS 2019 occupation codes. These estimates tend to be quite low with a mean lower than 10 percent and a 95 percent quantile of 8 percent. The larger values are almost exclusive to the landmark occupations shown in table 2.

3.3 Markup and Additional Adjustments

Markup. We estimate the full production costs by multiplying the data-related wage bill by a markup (i.e., the α in equations 1 and 6) that is designed to reflect employee benefits, capital costs, and intermediate consumption, none of which are included in the wage bill. Observing publicly available information, firms engaged in data aggregation, data sales, and other data-related market activities appear generally to be classified to industries in Information (NAICS 51) and Professional, Scientific and Technical (PST) Services (NAICS 54).[7] Based on these observations, we use Data Processing and Hosting (NAICS 518), Other Information Services (NAICS 519), and Computer Systems Design (NAICS 5415) as the representative industries for the markup.

We calculate α as a composite ratio of compensation, intermediate consumption (excluding materials), consumption of fixed capital (CFC), and net operating surplus to wages and

[7]For example, Axciom, Facebook, Localeze, and Burning Glass Technologies appear to be classified to NAICS 51 industries. In addition, Alphabet, Foursquare, Infogroup, Nielsen, Automatic Data Processing Inc. (ADP), The NPD Group, and International Data Corporation (IDC) all appear to be classified to NAICS 54 industries. Exceptions are the credit bureaus, which are classified to Administrative & Support Services (NAICS 56) industries.

Table 3: Effective factors applied to the wage bill

NAICS	Markup	Capital formation	Purchased data	Effective factor
518	2.52	0.50	0.50	0.63
All other	2.52	0.50	N/A	1.26

Note: The table summarizes by NAICS subsector the effective factors that are applied to the wage bill to calculate the full production costs. *All other* excludes NPISH and general government: Educational Services (NAICS 61), Health Care and Social Assistance (NAICS 62), Arts, Entertainment and Recreation (NAICS 71), Religious, Grantmaking, Civic, Professional, and Similar Organizations (NAICS 813), and Public Administration (NAICS 92).

salaries using data summed for select industries from BEA's annual industry accounts. In other words, the composite ratio is weighted by the size of the chosen industries. The average annual ratio is 2.52. For our experimental results, we use 2.52 as a time-invariant markup for each year 2002–2021.

Additional Adjustments. We do not have an estimate of own-account data output that is used up in current production versus own-account data output that is used in capital formation. Thus, we reduce the full production cost estimate by 50 percent to capture capital formation.

We also adjust for potential overlap between data assets and R&D assets by reducing the estimated time-use factor for data-relevant activities based on ratios of R&D employees. Likewise, in addition to excluding software skills in the estimation of time-use factors, we assign a zero percent time-use factor for data-relevant activities to the occupations BEA uses to estimate own-account software – Computer Systems Analysts (15-1211), Computer Programmers (15-1251), Software Developers (15-1252), and Software Quality Assurance Analysts (15-1253) – to avoid potential overlap between data assets and software assets.[8] Finally, we adjust for overlap between own-account data and purchased data by further reducing the adjusted production cost estimate for Data Processing and Hosting (NAICS 518) by 50 percent.

We choose 50 percent as a placeholder for capital formation and purchased data ad-

[8]Occupational codes correspond to the BLS OEWS/EP 2021 taxonomy.

justments to reflect our acknowledgment of the adjustments until future empirical evidence comes available. Table 3 summarizes the effective factors that are applied to the wage bill to calculate investment in data assets for our core experimental results. Section 4 has more discussion on the markup and additional adjustments.

4 Addressing Measurement Challenges

The main challenges for measurement of own-account data stocks and flows that we address in the paper are similar to challenges imposed by other own-account IPPs that are already included in capital formation in the *SNA* and the U.S. NIPAs. We identify here four challenges and how we address the challenges for own-account data.

4.1 Scope of Costs in Capital Formation

The scope of costs to include in capital formation is important for own-account data and other own-account IPPs.[9] The stages of the data value chain (OECD 2013; Moro Visconti et al. 2017) yield insights into activities that underlie the production process for data – including collection, storage, processing, distribution, and usage – some of which are reflective of costs that embody capital formation. The scope that has been recently introduced by the OECD (2021) is that capital formation should include both recording and processing costs and the costs of procuring access to data. Procurement costs may include either explicit purchases or the value of "free" digital products exchanged for access.[10]

We address this challenge by identifying skills in the BGT taxonomy that are relevant to data-related activities, including data entry, storage, analysis, and management. These

[9]For example, OECD (2010) identifies eight stages of activities in the production of own-account software: feasibility analysis, functional analysis, detailed analysis, programming, tests, documentation, training, and maintenance. Of the eight stages, only costs for functional analysis, detailed analysis, programming, tests, and documentation are within scope for capital formation.

[10]The latter procurement costs are identified in Farboodi and Veldkamp (2021) as a measurement challenge, and their model moves beyond price-based valuation by assigning a value to goods and data that have a zero transaction price.

skills are embodied by the occupations that underlie our estimates of the data wage bill. In addition, we reduce the full production cost estimate for data by 50 percent to account for data-related output that is used up in the current period and never becomes capital formation.[11]

4.2 Multiple Counting

Own-account data and other own-account IPPs are at risk of multiple counting from several sources.

4.2.1 Overlap Among Categories of IPPs

One source of multiple counting is overlap among categories of IPPs that are separately measured, such as data, software, and research and development (R&D).

Software. We address the overlap between data and software by estimating the time-use factors for data, which are intentionally based on unique data-relevant skills that are distinguishable from software-relevant skills. In addition, we completely exclude from the data wage bill the wages of the occupations that BEA uses to estimate own-account software–Computer Programmers, Computer Systems Analysts, Software Developers, and Software Quality Assurance Analysts.[12] For comparison with data-relevant skills presented in table 1, table 4 presents the top 80 BGT skills identified as software relevant. Likewise, table 5 shows the top time-use factors for occupations engaged in software-related activities to compare with landmark occupations for data reported in table 2.

While tables 1 and 4 demonstrate no overlap for BGT skills by design, there is overlap

[11] Another approach would be to use a depreciation rate for data that reflects a more rapid decline in value of investment flows as a result of obsolescence. However, such an approach would disregard the accounting difference between intermediate consumption and consumption of fixed capital.

[12] The time-use factors for these occupations are relatively modest - each less than 20 percent - and we think the occupations may reasonably embody some data-related activities that accompany own-account software development but are not included in BEA's measures of own-account software. However, we choose to completely exclude the occupations for a more conservative estimate.

of seven occupations with high time-use factors in tables 2 and 5. The occupations that show up in both tables include Business Intelligence Analysts, Computer and Information Research Scientists, Database Administrators, Database Architects, Data Warehousing Specialists, Geographic Information Systems Technicians, and Statisticians. In addition, the data and software time-use factors sum to more than 100 percent for the first five occupations, which implies the occupations and their time-use factors may be used to measure either data- or software-related activity but not both. However, there is no overlap between landmark occupations for data and the occupations BEA currently uses to estimate own-account software.

Overlap is expected when activities are intertwined. One example is software and R&D. Based on the 2018 Business Enterprise Research and Development Survey (BERD) table 19, $165.6 billion (37.5 percent) of domestic R&D was software products and embedded software R&D.[13] In the NIPAs, this overlap is included with R&D investment and excluded from software investment. There may also be job activities at the intersection of data, software, and R&D, such as software programming to prepare a data set for research. Observing independently-estimated time-use factors that together exceed 100 percent is not problematic in itself for our estimates because we know that own-account software estimation is limited to four specific occupations with relatively low time-use factors. However, the outcome does suggest an incentive to jointly estimate own-account data and own-account software to ensure consistency and prevent double counting if the scope of own-account software is expanded to include more occupations in the future.

[13] According to guidance in the BERD survey, R&D activity in software includes 1) software development or improvement activities that expand scientific or technological knowledge and 2) construction of new theories and algorithms in the field of computer science. Likewise, the BERD survey requires that R&D activity in software exclude 1) software development that does not depend on scientific or technological advance, such as supporting or adapting existing systems, adding functionality to existing application programs, and routine debugging of existing systems and software, 2) creation of new software based on known methods and applications, 3) conversion or translation of existing software and software languages, and 4) adaptation of a product to a specific client, unless knowledge that significantly improved the base program was added in that process.

Table 4: BGT skills identified as software relevant

.NET	Microsoft Sql Server Integration Services (SSIS)
Active Server Pages (ASP)	Microsoft Visio
Agile Development	Middleware
AJAX	MySQL
Amazon Web Services (AWS)	Object-Oriented Analysis and Design (OOAD)
AngularJS	Oracle
Apache Hadoop	Oracle PL/SQL
Apache Tomcat	PERL Scripting Language
Apache Webserver	Platform as a Service (PaaS)
Application Design	Python
ASP.NET	Relational DataBase Management System (RDBMS)
Atlassian JIRA	Ruby
C++	Salesforce
COBOL	SAP
Computer Engineering	SAS
Crystal Reports	Scrum
Debugging	Shell Scripting
Eclipse	Software Architecture
Enterprise Resource Planning (ERP)	Software as a Service (SaaS)
Extensible Markup Language (XML)	Software Development
Extensible Stylesheet Language XSL	Software Engineering
Firmware	Software Testing
Git	SQL
HTML5	SQL Server
Hypertext Preprocessor (PHP)	SQL Server Reporting Services (SSRS)
IBM WEBSPHERE	Systems Analysis
Informatica	Systems Development Life Cycle (SDLC)
Java	Teradata DBA
Java Server Pages (JSP)	Transact-SQL
JavaScript	Unified Modeling Language (UML)
JavaScript Object Notation (JSON)	UNIX
jQuery	UNIX Shell
JUnit	User Acceptance Testing (UAT)
Linux	User Interface (UI) Design
Microsoft Access	Visual Basic
Microsoft Azure	Visual Studio
Microsoft C#	VMware
Microsoft Operating Systems	Waterfall
Microsoft Project	WebLogic
Microsoft SQL	Windows Server

Note: Top 80 software skills by frequency identified from landmark occupations.

Table 5: Top time use factors for software

O*NET SOC 2010	Description	Time use factor
15-1133.00	**Software Developers, Systems Software**	**0.95**
15-1132.00	**Software Developers, Applications**	**0.94**
15-1131.00	**Computer Programmers**	**0.85**
15-1121.00	**Computer Systems Analysts**	**0.82**
15-1134.00	Web Developers	0.65
15-1199.02	Computer Systems Engineers/Architects	0.60
15-1199.08	Business Intelligence Analysts	0.55
15-1199.06	Database Architects	0.55
15-1141.00	Database Administrators	0.52
15-1199.01	Software Quality Assurance Engineers and Testers	0.52
15-1199.09	Information Technology Project Managers	0.50
15-1143.00	Computer Network Architects	0.49
13-1111.00	Management Analysts	0.48
15-1199.07	Data Warehousing Specialists	0.46
15-1111.00	Computer and Information Research Scientists	0.45
15-1142.00	Network and Computer Systems Administrators	0.41
15-1199.00	Computer Occupations, All Other	0.40
15-1122.00	Information Security Analysts	0.40
11-3021.00	Computer and Information Systems Managers	0.39
17-2061.00	Computer Hardware Engineers	0.38
15-1199.04	Geospatial Information Scientists and Techs	0.38
15-1199.03	Web Administrators	0.37
15-1152.00	Computer Network Support Specialists	0.37
15-1151.00	Computer User Support Specialists	0.36
15-2041.00	Statisticians	0.34
13-2099.01	Financial Quantitative Analysts	0.32
15-1199.11	Video Game Designers	0.32
15-1143.01	Telecommunications Engineering Specialists	0.32
17-3029.07	Mechanical Engineering Technologists	0.30
17-1011.00	Architects, Except Landscape and Naval	0.30
13-2051.00	Financial Analysts	0.28
15-1199.10	Search Marketing Strategists	0.28
13-1081.02	Logistics Analysts	0.28
17-2199.08	Robotics Engineers	0.27
27-1021.00	Commercial and Industrial Designers	0.27
27-3042.00	Technical Writers	0.27
17-3031.02	Mapping Technicians	0.27
15-1199.05	Geographic Information Systems Technicians	0.27

Note: Bold occupations denote landmark occupations that are by design the same occupations BEA currently uses to estimate own-account software. Software Developers (systems software) and Software Developers (applications) are combined into Software Developers and Software Quality Assurance Analysts in SOC 2018.

Research & Development. In contrast to software, the BGT skills dataset does not include R&D-relevant skills to distinguish them from data-relevant skills, which may yield some overlap between data assets and R&D assets. For example, Goodridge et al. (2021) and Statistics Canada (2019a) both argue that data science activities meet the *SNA* and OECD (2015) definition of R&D. However, Goodridge et al. (2021) suggest that data science is not included in measured R&D in practice by some countries because R&D is generally measured based on surveys designed for known performers of traditional scientific R&D activities. Likewise, Statistics Canada (2019a) suggests that the survey they use to measure R&D needs to be examined for updates because the survey was developed years ago and is biased toward the selection of firms engaged in more traditional forms of R&D activities, such as pharmaceutical firms, and biased away from a growing number of firms in diverse industries engaged in data science activities.

For R&D measures in the U.S. national accounts, the survey used to collect information on performance of business R&D is the BERD survey.[14] The 2019 BERD survey explicitly includes software development or improvement activities that expand scientific or technological knowledge and construction of new theories and algorithms in the field of computer science. In addition, the 2019 BERD survey asks respondents to report the percentage of domestic R&D expenditures paid for and performed by them that was for artificial intelligence (AI), which includes speech recognition, machine vision, machine learning, text analytics, and natural language generation and processing. Thus, data science may not be absent in practice from the BERD survey and may be included in BEA's measures of R&D based on the BERD survey.

To adjust for potential overlap between data assets and measured R&D assets in our esti-

[14]The 2019 BERD survey defines research and development as follows: "*Research* is defined as experimental or theoretical work undertaken primarily to acquire new knowledge or understanding of phenomena and observable facts. Research may be either "basic", where the goal is primarily to acquire new knowledge or understanding of a given topic without a specific commercial application in mind, or "applied", where the goal is to solve a specific problem or meet a specific commercial objective. *Development* is defined as the systematic use of research and practical experience to produce new or improved goods, services, or processes. In simple terms, the intended output of research is ideas and the intended output of development is products."

mates, we reduce the time-use factor for data-relevant activities based on an estimate of the ratio of employees whose main work activity is R&D. We use a sample from the National Survey of College Graduates (NSCG), National Survey of Recent College Graduates (NSRCG), and Survey Doctorate Recipients (SDR) from 1993 to 2013 to estimate by occupation group the ratio of employees whose main work activity was R&D (Minnesota Population Center 2016). We then develop a crosswalk between the survey occupation groups and those in the latest taxonomy of the BLS OEWS/EP codes. We matched 249 out of the 834 occupation codes used in the wage bill with 26 of the NSF survey codes. For these 249 occupations, we adjust the time use factor as follows:

$$\hat{\tau_{\omega}}' = \hat{\tau_{\omega}} \left(1 - \hat{\rho_{\omega}}'\right) \tag{7}$$

where $\hat{\tau_{\omega}}'$ is the time-use factor for occupation ω adjusted for R&D, $\hat{\tau_{\omega}}$ is the original time-use factor, and $\hat{\rho_{\omega}}'$ is the corresponding share of employees for occupation ω in the NSF surveys that reported R&D as the primary work activity based on the share of time allocated to it.[15]

4.2.2 Non-Rival Use of Data

Another source of multiple counting is overlap between own-account data and purchased data, which is also a source of multiple counting for software and R&D. We address this challenge by further reducing the adjusted production cost estimate by 50 percent for Data Processing and Hosting (NAICS 518), which is the NAICS code with data-related activities closest to those we measure under our methodology.[16]

Finally, a source of multiple counting that has been cited as a concern specifically for data

[15] As an alternative, we also consider completely excluding from the data wage bill the wages of four SOC 2010 occupations that appear to be R&D occupations based on "research" in the descriptions: Computer and Information Research Scientists (SOC 15–1111), Operations Research Analysts (SOC 15–2031), Survey Researchers (SOC 19–3022), and Social Science Research Assistance (SOC 19–4061). However, we think the occupations may reasonably embody some data-related activities that accompany R&D, and we are not able to determine if excluding these four occupations based on "research" is as comprehensive as adjusting based on the ratios.

[16] The reduction for Data Processing and Hosting (NAICS 518) to adjust for non-rival use of data is in addition to the reductions for software and R&D overlap.

Table 6: Weighted composite ratio for full sum-of-costs

	Ratio	Share (%)
Compensation	1.15	46
Intermediate consumption	0.81	32
Consumption of fixed capital	0.29	11
Net operating surplus	0.27	11
Markup	2.52	

Note: All data are from BEA's annual industry accounts. Intermediate consumption excludes materials. The table reports the simple average for 2002-2021 of each annual measure summed for NAICS 518-519 and NAICS 5415 divided by annual wages and salaries summed for the same industries.

as an asset is that the same piece of information can be used in multiple databases. However, a single piece of information is transformed when it is added to a record with other pieces of information. Likewise, we are not valuing pieces of information but rather the activities associated with making the information available in a record, which is unique to every firm for own-account measures.

4.3 Measuring Capital Costs

A challenge that may be more relevant (but not unique) to data stocks and flows is how to measure the capital cost component in the sum-of-costs. There is a question of what proportions of the sum-of-costs should be accounted for by labor costs, capital costs, and intermediate consumption, given the role of capital services in the collection, storage, analysis, and management of data.

We apply a markup of 2.52 to the wage bill as explained in section 3.3. Since the markup is a weighted composite ratio of compensation, intermediate consumption (excluding materials), CFC, and net operating surplus, we can decompose the markup into the proportionate share of each component in the sum-of-costs. The decomposition is presented in table 6.

4.4 Prices and Depreciation

Own-account data are not transacted in active markets, which means there are no observed transactions that are useful for measuring prices and depreciation. We utilize international guidelines and U.S. practice for deflating and depreciating own-account software and databases as a starting point for deflating and depreciating own-account data, which reflects the inclusion of own-account data as a subcategory of software and is consistent with preliminary guidance emerging from the *SNA* community's current work on revising the *SNA*.

Prices. In the absence of deflators for own-account software, OECD (2010) recommends that deflators for custom software be used as a proxy until own-account software deflators are developed. In addition, OECD (2010) suggests three options for own-account database deflators. One option is to use a price index of a related activity for which there is a price index of reasonable quality. The other two options are an input cost index, one with zero productivity growth and another with an adjustment based on productivity growth of a similar industry. BEA does not compile a price index for own-account databases because own-account databases are not measured separately from own-account software in the U.S. NIPAs. For own-account software, BEA currently compiles a price index from a weighted average of the prepackaged software price and a BEA input cost index (U.S. Bureau of Economic Analysis 2020). The input cost index is compiled from BLS data on wage rates for Computer Programmers and Computer Systems Analysts and the intermediate consumption associated with the production of software. The input cost index reflects an explicit adjustment for changes in productivity that is based primarily on a BLS total factor productivity index.[17]

To address the lack of prices for own-account data, we develop an experimental price index. The price index follows BEA's own-account software price index methodology by estimating a composite wage rate series and an intermediate input cost series. For the wage

[17]When BEA first introduced capital measures of own-account software into the NIPAs in 1999, an input cost index was compiled from a weighted average of compensation rates for Computer Programmers and Computer System Analysts and the intermediate consumption associated with their work (Moulton and Sullivan 1999). No productivity adjustment was made.

series we use the effective wage bill from our estimates of investment in data assets. In other words, we use the time-use factors for each occupation in the business sector adjusted for R&D and software overlap. To obtain the composite wage rate series we use the following equation:

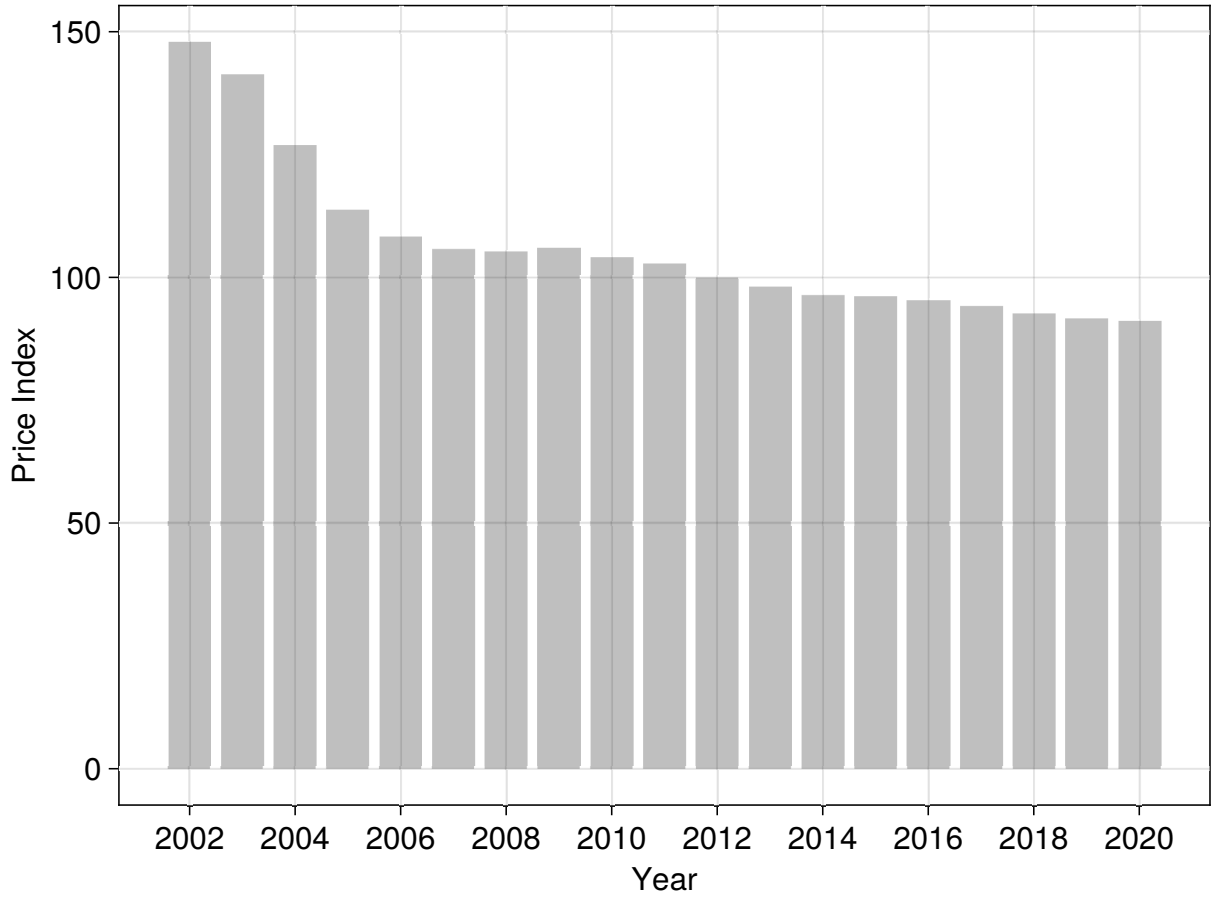
$$r_t = \frac{\sum W_{\omega,i,t} H_{\omega,i,t} \hat{\tau_\omega}'}{\sum H_{\omega,i,t} \hat{\tau_\omega}'} \tag{8}$$

where the composite wage rate at year t, r_t, is given as the effective wage bill over the number of employees. $W_{\omega,i,t}$ denotes the average wage for occupation ω at year t for industry i and $H_{\omega,i,t}$ the number of employees for the same occupation, industry, and year. Lastly, $\hat{\tau_\omega}'$ is the effective time-use factors adjusted for overlap with software and R&D.

In addition to the composite wage rate, the input-cost price index includes a cost component for intermediate inputs based on intermediate consumption for Data Processing and Hosting (NAICS 518) and Computer Systems Design (NAICS 5415). We also adjust the input-cost price index for total factor productivity growth published by BLS for Data Processing and Hosting and Computer Systems Design, which are weighted by industry gross output. Finally, we combine our productivity-adjusted input-cost index in a simple average with the average industry price index weighted by industry gross output for Data Processing and Hosting and Computer Systems Design. The resulting experimental price index for own-account data is presented in figure 1 where 2012 is the base year.

Depreciation. OECD (2009) recommends several options for determining depreciation parameters for an asset class, which generally requires information on prices or service lives. One option uses information on the service life and makes an additional assumption about the functional form of the depreciation pattern. A functional form that is commonly used for pragmatic reasons is the geometric model of depreciation, which yields a pattern of constant percentage decline in an asset's value. In the absence of econometric estimates of the geometric depreciation rate, the geometric depreciation rate can be estimated using a simple

Figure 1: Own-account data price index



declining balance method as $\delta = R \,/\, S$, where R is an estimated declining balance rate and S is an average service life (Hulten and Wykoff 1996). The declining balance rate may be either estimated econometrically or is sometimes assumed to be 2. For software and databases, OECD (2010) recommends the average service life be obtained by surveying software users, surveying software suppliers, or hiring software consultants. BEA does not compile a measure of depreciation for own-account databases but does compile a measure of depreciation for own-account software for the U.S. Fixed Assets Accounts (FAAs). To estimate depreciation for own-account software, BEA uses a 5-year service life and a declining balance rate of 1.65 to determine the geometric depreciation rate. The service life is based on estimates of the relationship between computer expenditures and software expenditures, anecdotal evidence about how long software is used before replacement (including an informal survey of business uses of software), and tax-law-based service lives of software.[18] The declining balance rate is borrowed from the Hulten-Wykoff methodology that is used for most equipment in the FAAs (Hulten and Wykoff 1981; Hulten, McCallum, et al. 1981; Wykoff and Hulten 1979; Fraumeni 1997). To address the lack of depreciation rate for own-account data, we use BEA's current geometric depreciation rate of 0.33 for own-account software as a proxy.

5 Results

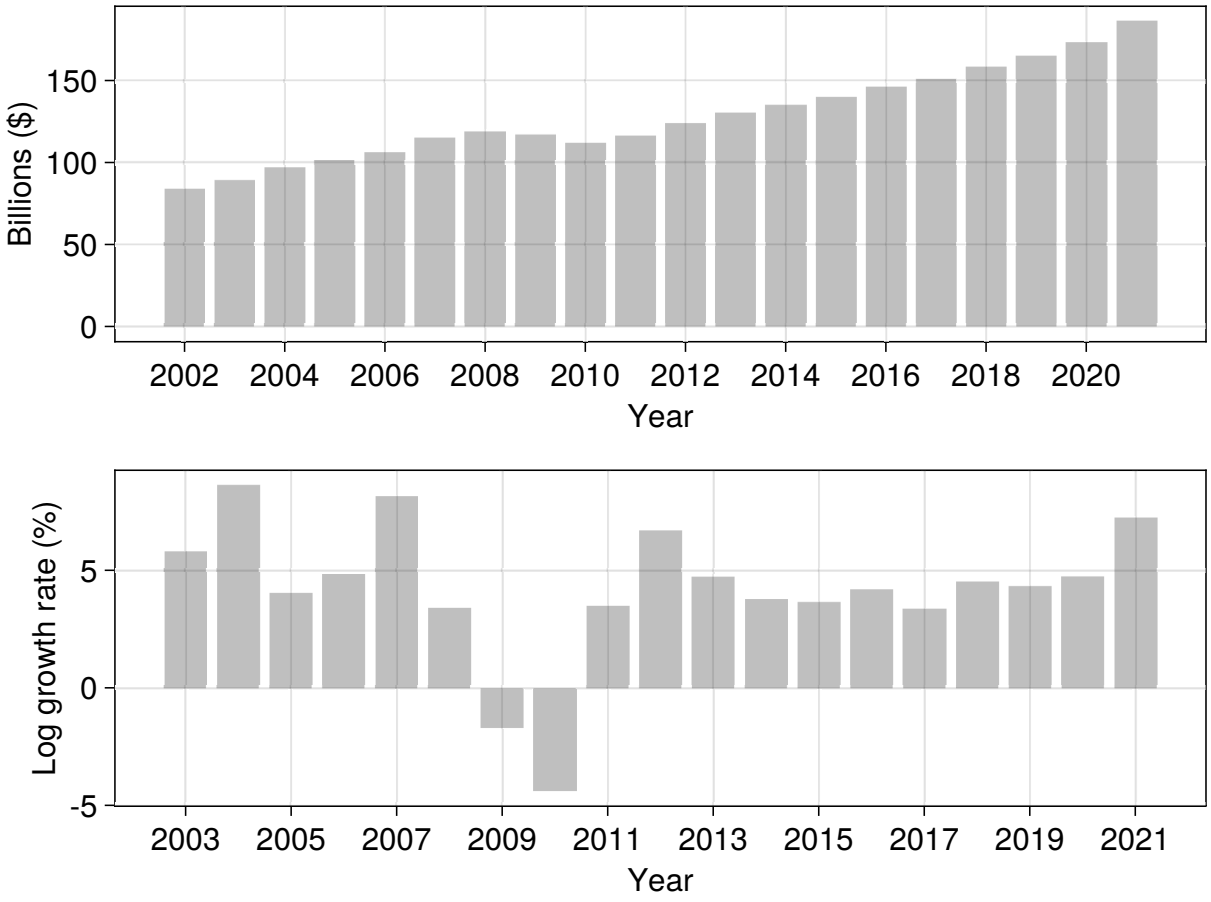
5.1 National Aggregates

5.1.1 Experimental Current-Dollar and Historical-Cost Estimates

Experimental estimates for aggregate business sector current-dollar investment in data assets for 2002–2021 are presented in figure 2. The upper panel in the figure reflects current-dollar levels and the lower panel reflects current-dollar log growth rates. Estimated current-dollar investment in 2002 is $84 billion and in 2021 is $186 billion. Growth of current-dollar

[18] A summary of BEA's depreciation estimates is available at: `https://apps.bea.gov/national/pdf/BEA_depreciation_rates.pdf`.

Figure 2: Current-dollar annual investment in data assets



investment is as high as 8.6 percent for 2004 and as low as −4.4 percent for 2010. The average annual growth rate in current-dollar investment for 2003–2021 is 4.2 percent. Prior to the recession of 2007–2009, the average annual growth rate for 2003–2007 was 6.3 percent, which declined to 3.4 percent for 2008–2021. Average annual growth for the ten-year period 2012–2021 was 4.7 percent.

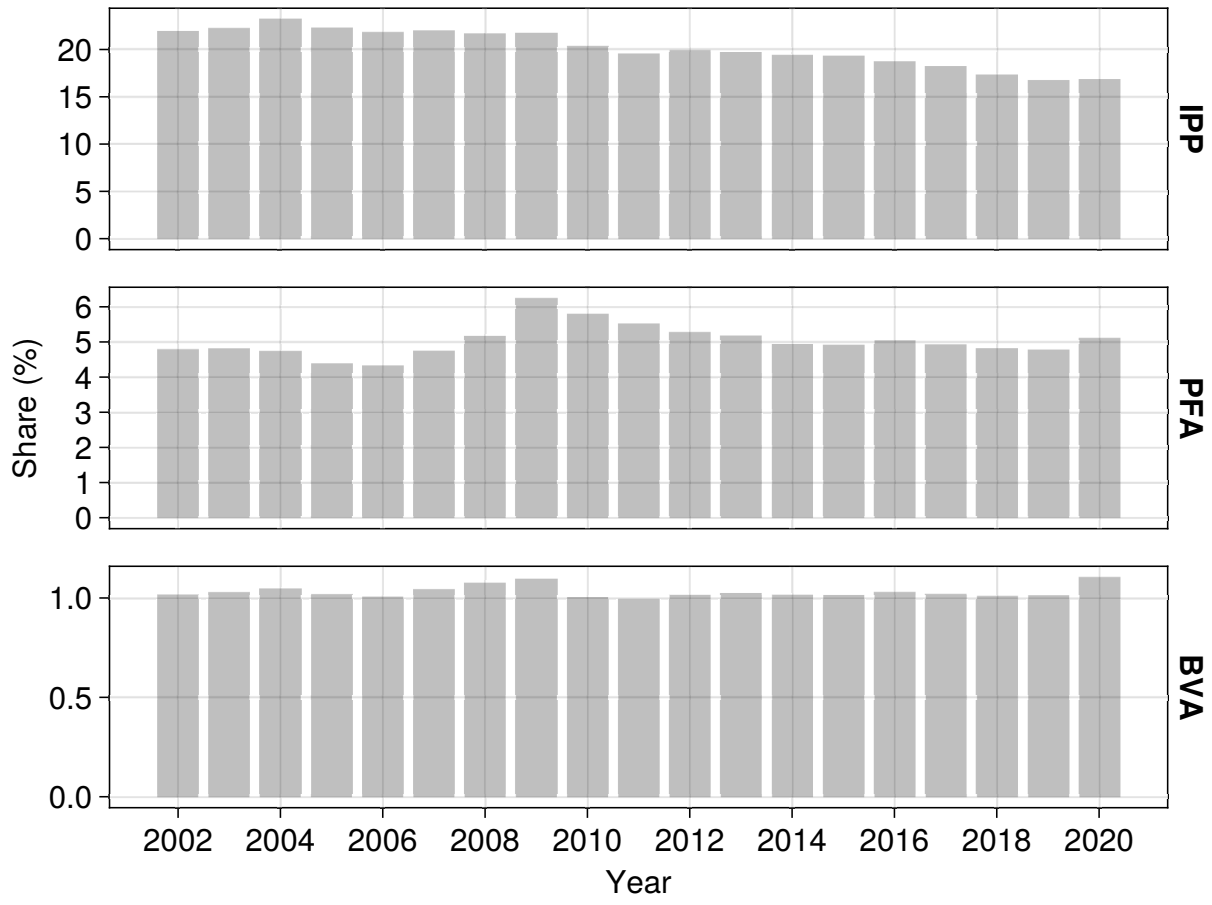
Current-dollar investment in data assets as a share of NIPA current-dollar business sector value-added (BVA) is reported in figure 3. The share of data investment for the period averages 1.0 percent of business sector value-added. We also report in figure 3 current-dollar investment in data assets as a share of NIPA current-dollar investment in IPPs and as a share of NIPA current-dollar investment in private fixed assets. Data investment as a share of investment in IPPs declines over the period from 22.0 percent in 2002 to 16.9 percent in 2020 - the share averages 20.2 percent for the period. Data investment as a share of investment in private fixed assets is 4.8 percent in 2002 and 5.1 percent in 2020 with some variation over the period - the share averages 5.0 percent for the period.

Experimental estimates for aggregate business sector historical-cost net stocks of data assets for 2002–2021 are presented in figure 4. The historical-cost net stocks are calculated using a perpetual inventory method (PIM) with geometric depreciation. The PIM is a sum of annual depreciated historical-cost investment in data assets. Annual historical-cost investment in data assets prior to 2002 is backcast using the annual growth in current-dollar investment in own-account software as an indicator. Depreciation of annual historical-cost investment is calculated using BEA's depreciation rate for own-account software of 0.33, assuming new investment in data assets is placed in service at midyear. The calculation for annual depreciated historical-cost investment, i.e., net stock N, in year t for investment I placed in service in year h can be summarized as follows:

$$N_{t,h} = I_h \left(1 - \frac{\delta}{2}\right) (1 - \delta)^{t-h} . \tag{9}$$

The upper panel in figure 4 reflects historical-cost levels and the lower panel reflects

Figure 3: Investment in data assets as a share of NIPA aggregates



Note: The numerator for each share is the current-dollar investment in data assets. The denominator for each share is the current-dollar NIPA aggregate plus the current-dollar investment in data assets. Business sector value-added (BVA) is from line 2 of "National Income and Product Accounts: Table 1.3.5. Gross Value Added by Sector". Investment in intellectual property products (IPP) is from line 1 of "Fixed Assets Accounts: Table 3.7I. Investment in Private Intellectual Property Products by Industry", adjusted to exclude NPISH by subtracting lines 66, 67, and 72. Investment in private fixed assets (PFA) is from line 1 of "Fixed Assets Accounts: Table 3.7ESI. Investment in Private Fixed Assets by Industry", adjusted to exclude NPISH by subtracting line 66, 67, and 72.

Figure 4: Historical-cost annual net stocks of data assets

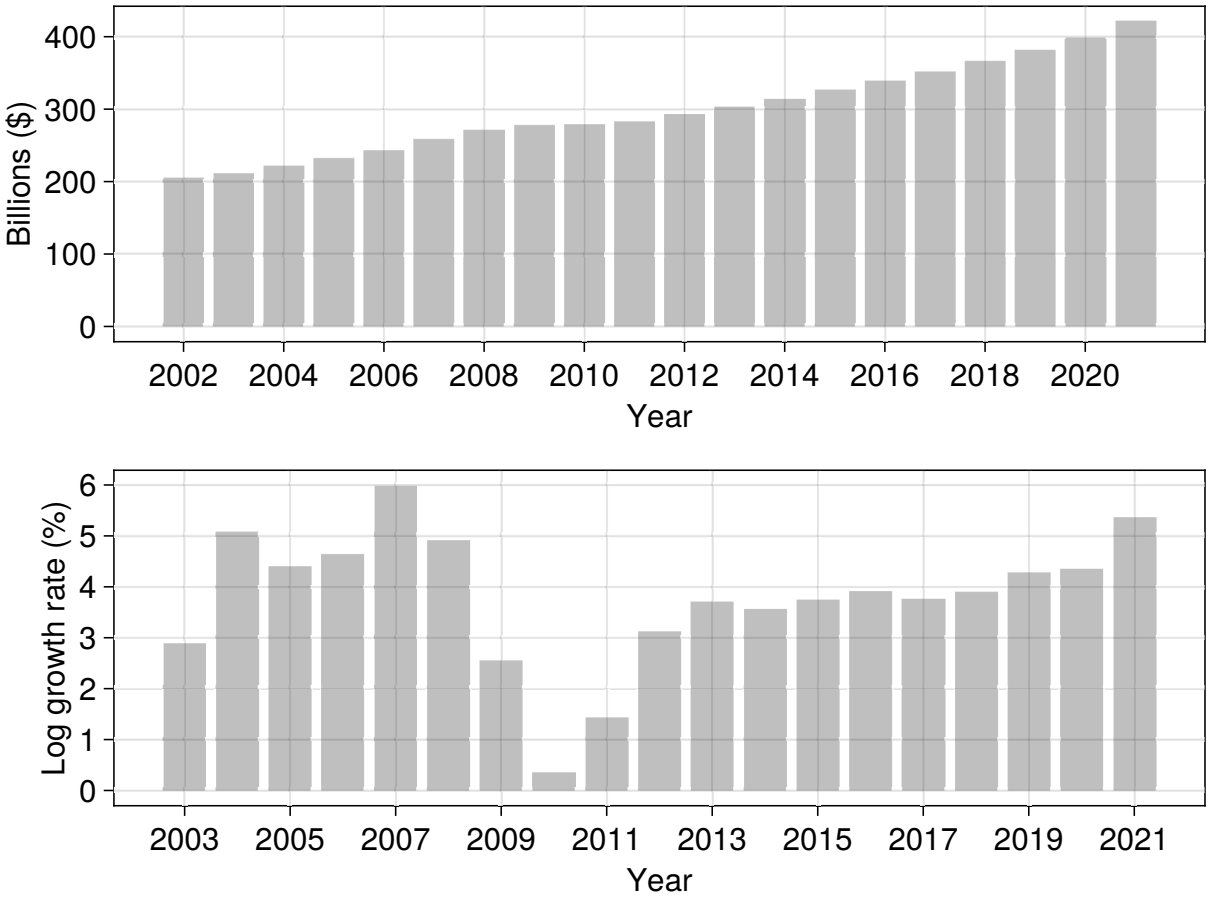


Table 7: Growth in real measures with and without investment in data assets 2003–2020 (%)

	Average			Cumulative		
	With data	W/o data	Δ	With data	W/o data	Δ
Data	7.47			134.42		
Value-added	1.99	1.95	0.04	35.89	35.15	0.74
IPPs	5.28	4.97	0.31	95.08	89.48	5.60
Software	7.45	7.71	−0.26	134.07	138.72	−4.65

Note: The table reports average and cumulative log growth rates in real data investment along with changes in growth for business sector real value-added, private sector real investment in IPPs, and private sector real investment in software with and without data investment for 2003–2020. Aggregate price indexes are recalculated using Törnqvist expenditure shares.

historical-cost log growth rates. Estimated historical-cost net stock in 2002 is $205 billion and in 2021 is $421 billion. Growth of historical-cost net stocks is as high as 6.0 percent for 2007 and as low as 0.4 percent for 2010. The average annual growth rate in historical-cost net stocks for 2003–2021 is 3.8 percent.

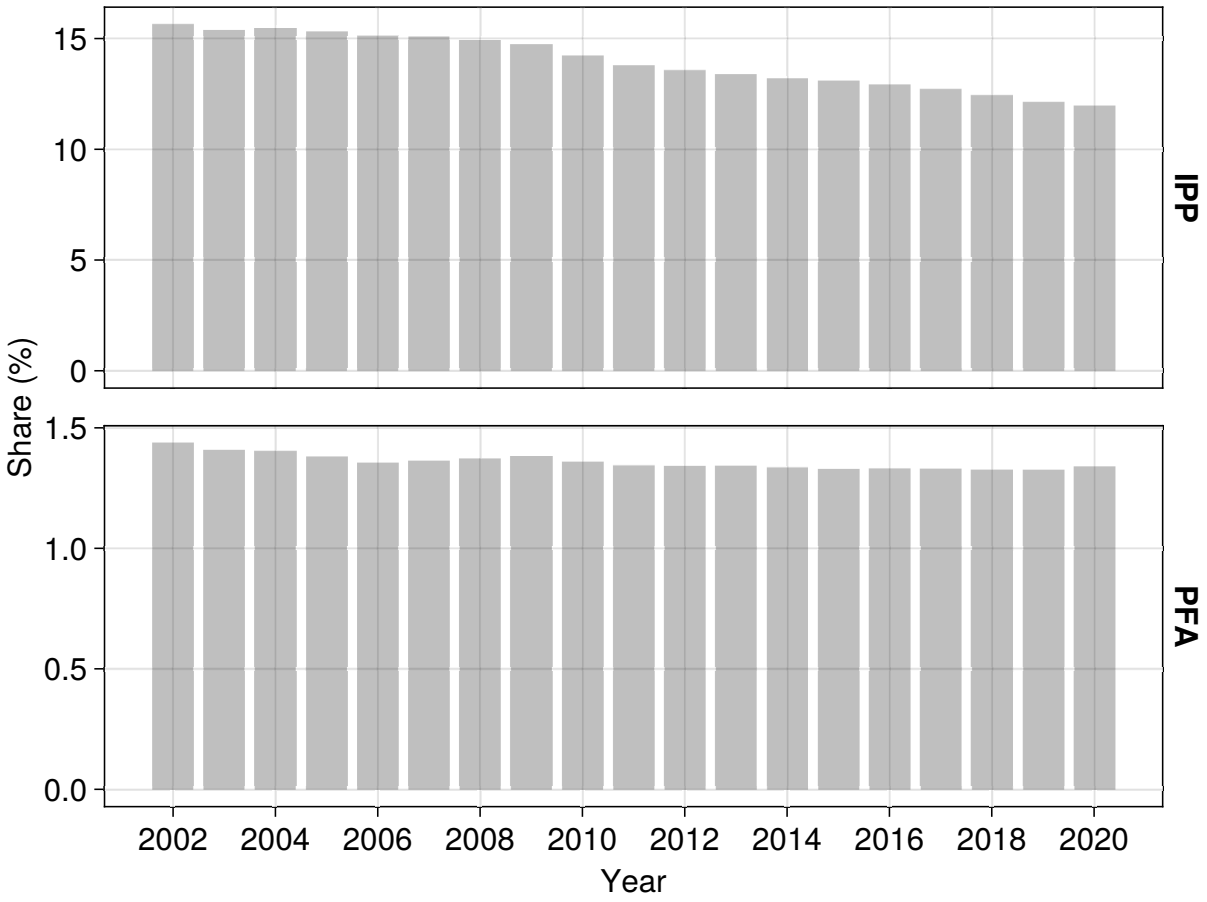
We report the historical-cost net stocks of data assets as a share of the FAA historical-cost net stocks of IPPs and as a share of the FAA historical-cost net stocks of private fixed assets in figure 5. Data stocks as a share of IPP stocks decline over the period from 15.6 percent in 2002 to 12.0 percent in 2021 - the share averages 13.9 percent for the period. Data stocks as a share of private fixed assets stocks is 1.4 percent in 2002 and 1.3 percent in 2021 with some variation over the period - the share averages 1.4 percent for the period.

5.1.2 Real Growth

We compare the log growth in real U.S. aggregate measures with and without our experimental estimates of business sector investment in data assets for 2003–2020. Real aggregate measures include business sector value-added, private sector investment in IPPs, and private sector investment in software. We recalculate measured aggregate prices using Törnqvist expenditure shares. We report average and cumulative annual growth in table 7.

The average annual growth in real data investment for 2003–2020 is 7.5 percent and the cumulative annual growth for the period is 134.4 percent. When data investment is added

Figure 5: Net stocks of data assets as a share of FAA aggregates



Note: The numerator for each share is the historical-cost net stock of data assets. The denominator for each share is the historical-cost FAA aggregate plus the historical-cost net stock of data assets. Net stocks of intellectual property products (IPP) are from line 1 of "Fixed Assets Accounts: Table 3.3I. Historical-Cost Net Stock of Private Intellectual Property Products by Industry", adjusted to exclude NPISH by subtracting lines 66, 67, and 72. Net stocks of private fixed assets (PFA) are from line 1 of "Fixed Assets Accounts: Table 3.3ESI. Historical-Cost Net Stock of Private Fixed Assets by Industry", adjusted to exclude NPISH by subtracting lines 66, 67, and 72.

to business sector value-added, the average annual change in real value-added growth over the period is an increase of 4 basis points, and the cumulative annual change is an increase of 74 basis points. When data investment is added to IPP investment, the average annual growth in real investment in IPPs for 2003–2020 is 31 basis points higher, and the cumulative average annual growth is 560 basis points higher. In contrast, the growth of real investment in data is lower than software investment, so the declines in average annual growth in real investment in software for the period is 26 basis points and in cumulative average annual growth is 465 basis points.[19]

In relation to other types of capital formation, data as an asset seems to grow relatively faster than R&D and entertainment, literary, and artistic originals. However, the software category of IPPs grows faster than data. One plausible explanation for this result is the complementary relationship between data and software. Software is an indispensable asset used for data-related activities such as transformations and analysis of data (e.g., data science). This could explain why software investment growth outpaces data investment growth because data assets increase the demand for software to make use of the data assets.

5.1.3 Shares of Investment by Occupation

In order to assess overlap between our estimates of data investment and investment in other IPPs - i.e., R&D and software - we calculate shares of investment in data by occupation. Table 8 reports shares of investment in data for occupations with more than 0.5 percent share for 2002–2021. We choose the cutoff to fit the table onto a single page. The 40 occupations in table 8 account for 68.4 percent of our investment estimate for the period. There are over 600 additional occupations included in our estimate but excluded from table 8. We note two observations in table 8. First, even if an occupation makes the list of landmark occupations in table 2 does not imply the occupation will account for a large share of the

[19]Goodridge et al. (2021) report labor productivity with and without data investment for 13 European Union countries and find a modest average increase in labor productivity of only 5 basis points with data investment for 2011–2016. The largest average annual increase by country is 9 basis points attributable to Germany, and the largest average annual decrease by country is 9 basis points attributable to Estonia.

Table 8: Occupational Shares of Investment in Data 2002-2021

OEWS 2021	Description	Share (%)
43-9061	Office Clerks, General	5.68
13-1111	Management Analysts	5.27
11-1021	General and Operations Managers	4.48
43-9021	Data Entry Keyers	4.26
11-3021	Computer and Information Systems Managers	4.15
43-3031	Bookkeeping, Accounting, and Auditing Clerks	3.28
43-4051	Customer Service Representatives	3.21
43-6014	Secs and Admin Assistants, Except Legal, Medical, and Executive	2.85
13-1161	Market Research Analysts and Marketing Specialists	2.68
15-1242	Database Administrators	2.58
15-1243	Database Architects	2.38
15-1244	Network and Computer Systems Administrators	2.18
11-3031	Financial Managers	2.17
13-2011	Accountants and Auditors	2.03
43-1011	First-Line Supervisors of Office and Admin Support Workers	1.73
15-1299	Computer Occupations, All Other	1.41
11-2021	Marketing Managers	1.12
15-1241	Computer Network Architects	1.12
11-9041	Architectural and Engineering Managers	1.05
15-1232	Computer User Support Specialists	0.94
11-1011	Chief Executives	0.90
13-1071	Human Resources Specialists	0.89
15-1221	Computer and Information Research Scientists	0.85
17-2112	Industrial Engineers	0.81
13-1082	Project Management Specialists	0.79
13-2051	Financial and Investment Analysts	0.77
41-4012	Sales Reps, Wholesale and Manufacturing, Except T&S Prods	0.71
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	0.71
11-2022	Sales Managers	0.71
15-1212	Information Security Analysts	0.69
43-3021	Billing and Posting Clerks	0.68
13-2054	Financial Risk Specialists	0.68
43-5071	Shipping, Receiving, and Inventory Clerks	0.66
41-3091	Sales Reps of Servs, Except Ads, Insurance, Fin Servs, and Tvl	0.64
43-6011	Executive Secretaries and Executive Administrative Assistants	0.60
13-1199	Business Operations Specialists, All Other	0.59
15-2031	Operations Research Analysts	0.59
13-1020	Buyers and Purchasing Agents	0.52
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	0.51
43-5061	Production, Planning, and Expediting Clerks	0.51
	Total	68.38

Note: Shares of investment in data are included for occupations with at least 0.5 percent share.

investment estimate. Two landmark occupations that do not make the cut-off for table 8 are *wellhead pumpers* and *hearing aid specialists*, which may be useful references to calculate a numeric similarity for non-landmark occupations but do not appear to play a big role in data investment. In contrast, landmark occupations like *data entry keyers* and *database administrators and architects* account for a large share of the data investment estimate. Second, R&D occupations and software occupations are mostly absent from table 8, which reflect the adjustments to exclude R&D employees and software occupations. Occupations with lower shares such as *computer and information research scientists* and *computer network architects* may contribute to capital formation in data as well as capital formation in R&D and software, but occupations with the highest shares are unlikely to contribute to capital formation in R&D and software.

5.2 NAICS Sector Aggregates

5.2.1 Experimental Current-Dollar Estimates

Experimental estimates for current-dollar investment in data assets by NAICS sector for 2002–2021 are presented in table 9. Table 10 reports the average annual growth in current-dollar investment in data assets by NAICS sector for 2003–2021. The current-dollar estimates as a share of current-dollar value-added by NAICS sector for 2002–2021 are shown in figure 6. Since our methodology starts with an estimate of the occupation-based wage bill, results by NAICS sector reflect industries that employ occupations engaged in data-related activities.

For the period 2002–2021, table 9 shows the total current-dollar investment in data was $2.6 trillion. The largest dollar investments were made in Professional, Scientific, and Technical (PST) Services ($646 billion), Manufacturing ($353 billion), and Finance and Insurance ($338 billion). The smallest dollar investments were made in Agriculture, Utilities, and Mining.

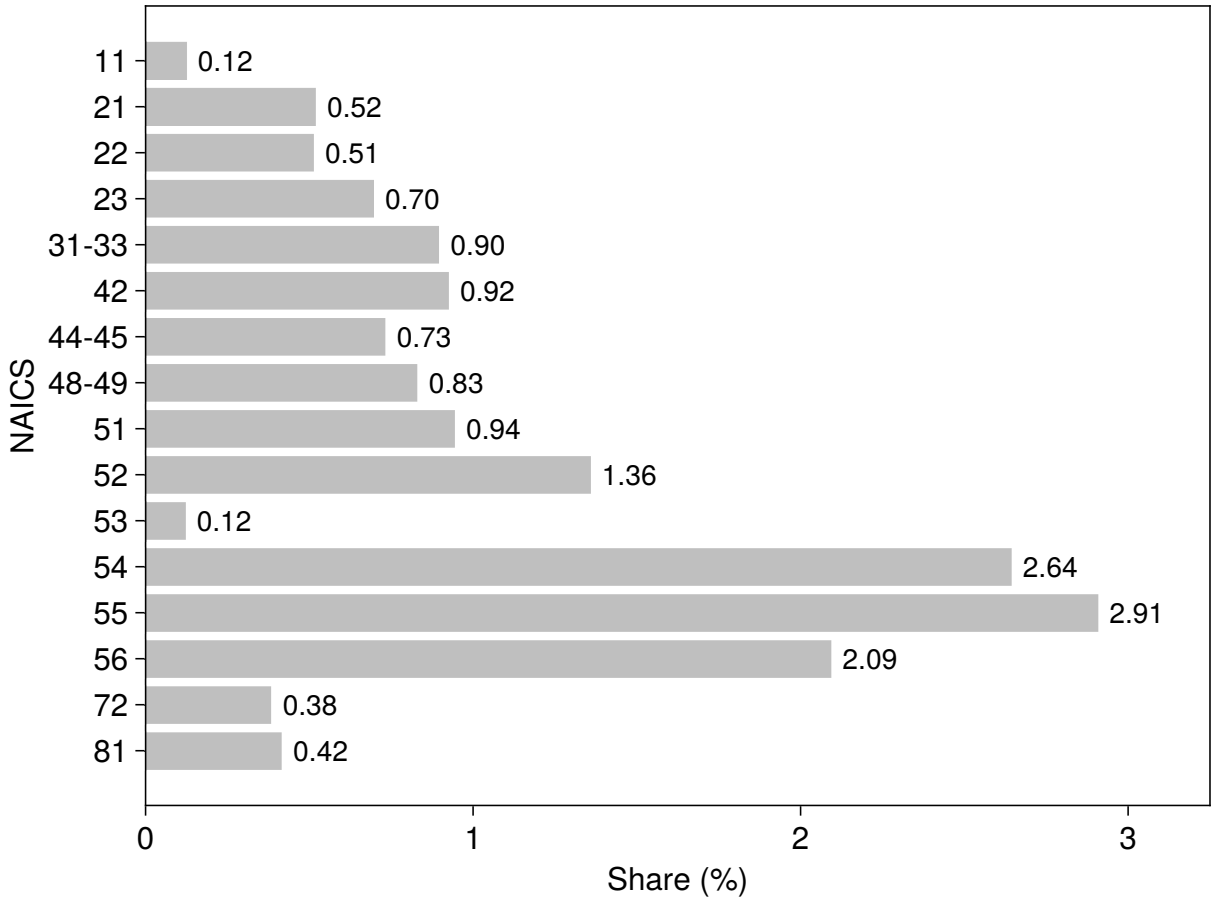
Table 10 demonstrates that average annual growth in current-dollar investment in data assets was as low as 2.1 percent for Manufacturing and as high as 6.2 percent for Management

Table 9: Current-dollar investment in data assets by NAICS sector 2002–2021

NAICS	**Description**	**($B)**
11	Agriculture, Forestry, Fishing and Hunting	4
21	Mining, Quarrying, and Oil and Gas Extraction	29
22	Utilities	28
23	Construction	95
31-33	Manufacturing	353
42	Wholesale Trade	183
44-45	Retail Trade	141
48-49	Transportation and Warehousing	81
51	Information	159
52	Finance and Insurance	338
53	Real Estate and Rental and Leasing	51
54	Professional, Scientific, and Technical Services	646
55	Management of Companies and Enterprises	179
56	Administrative & Support and Waste Management & Remediation Services	210
72	Accommodation and Food Services	36
81	Other Services (except Public Administration)	30
	Total	2,563

Note: Current-dollar estimates summed for 2002–2021 by NAICS sector. Estimates for NPISH and general government are excluded: Educational Services (NAICS 61), Health Care and Social Assistance (NAICS 62), Arts, Entertainment and Recreation (NAICS 71), Religious, Grantmaking, Civic, Professional, and Similar Organizations (NAICS 813), and Public Administration (NAICS 92).

Figure 6: Investment in data assets as a share of value-added by NAICS sector 2002–2021



Note: The numerator for each share is the current-dollar investment in data assets summed for 2002–2021. The denominator for each share is the current-dollar investment in data assets plus NAICS sector value-added summed for 2002–2021 from the U.S. Bureau of Economic Analysis, "Interactive Access to Industry Economic Accounts Data: Table 1 Value Added by Industry".

Table 10: Average annual growth in current-dollar investment in data assets by NAICS sector 2003–2021

NAICS	Description	(%)
11	Agriculture, Forestry, Fishing and Hunting	3.24
21	Mining, Quarrying, and Oil and Gas Extraction	4.07
22	Utilities	2.95
23	Construction	4.42
31-33	Manufacturing	2.14
42	Wholesale Trade	2.92
44-45	Retail Trade	2.37
48-49	Transportation and Warehousing	4.22
51	Information	4.17
52	Finance and Insurance	3.71
53	Real Estate and Rental and Leasing	3.95
54	Professional, Scientific, and Technical Services	6.24
55	Management of Companies and Enterprises	6.24
56	Administrative & Support and Waste Management & Remediation Services	3.43
72	Accommodation and Food Services	3.71
81	Other Services (except Public Administration)	3.95

Note: Annual log growth rates for current-dollar investment averaged for 2003–2021.

of Companies and PST Services. Average annual growth rates by NAICS sector exceeded the aggregate average annual growth rate of 4.2 percent for Construction (4.4 percent), Transportation and Warehousing (4.2 percent), PST Services (6.2 percent), and Management of Companies (6.2 percent).

In figure 6, the largest shares of NAICS sector value-added show up for Management of Companies (NAICS 55), Administrative Services (NAICS 56), PST Services (NAICS 54), and Finance and Insurance (NAICS 52). The smallest shares of NAICS sector value-added show up for Agriculture (NAICS 11), Real Estate (NAICS 53), Accommodation and Food Services (NAICS 72), and Other Services (NAICS 81).

5.2.2 Real Growth

We compare the log growth in real value-added for NAICS sectors with and without our experimental estimates of business sector investment in data assets for 2003–2020. We re-calculate measured NAICS sector prices using Törnqvist expenditure shares. We report

Table 11: Growth in real value-added with and without investment in data assets by NAICS sector 2003–2020 (%)

	Average			Cumulative		
NAICS	With data	W/o data	Δ	With data	W/o data	Δ
11	2.57	2.57	0.00	46.28	46.24	0.04
21	2.52	2.50	0.02	45.32	44.95	0.37
22	1.66	1.64	0.02	29.93	29.55	0.38
23	−0.68	−0.73	0.05	−12.22	−13.2	0.98
31-33	1.65	1.61	0.04	29.69	29.06	0.63
42	1.54	1.50	0.05	27.81	26.98	0.83
44-45	1.17	1.14	0.03	21.03	20.52	0.51
48-49	1.44	1.39	0.05	25.92	25.01	0.91
51	5.41	5.40	0.02	97.47	97.16	0.31
52	1.61	1.54	0.07	28.92	27.63	1.29
53	1.91	1.91	0.01	34.45	34.32	0.13
54	3.05	2.89	0.17	54.98	51.95	3.03
55	2.57	2.38	0.19	46.35	42.89	3.46
56	2.73	2.65	0.08	49.11	47.65	1.46
72	−0.51	−0.54	0.03	−9.2	−9.68	0.48
81	−1.15	−1.19	0.03	−20.74	−21.33	0.59

Note: The table reports average and cumulative log growth rates in real value-added by NAICS sector with and without data investment for 2003–2020. NAICS price indexes are recalculated using Törnqvist expenditure shares.

average and cumulative annual growth in real value-added growth by NAICS sector in table 11. Consistent with the result for business sector real value-added in table 7, the change in average annual growth is positive for each NAICS sector. When data investment is added, the largest increases in average real value-added growth show up for Management of Companies (NAICS 55, 19 basis points), PST Services (NAICS 54, 17 basis points), Finance and Insurance (NAICS 52, 7 basis points) and Administrative Services (NAICS 56, 8 basis points). Increases in cumulative real value-added growth are also largest for those NAICS sectors. The smallest increases in average and cumulative real value-added growth show up for Agriculture (NAICS 11), Mining (NAICS 21), Utilities (NAICS 22), Information (NAICS 51), and Real Estate (NAICS 53).

Table 12: Current-dollar investment in data assets for NPISH 2002–2021

NAICS	Description	($B)
61	Educational Services	149
62	Health Care and Social Assistance	329
71	Arts, Entertainment, and Recreation	23
813	Religious, Grantmaking, Civic, Professional, and Similar Organizations	51
	Total	552

Note: Current-dollar estimates summed for 2002–2021.

5.2.3 Non-profit Institutions Serving Households

While core experimental results for the paper are limited to the business sector, table 12 reports supplemental experimental results for current-dollar investment in data assets for NAICS sectors that represent the NPISH sector. For the period 2002–2021, table 12 shows the total current-dollar investment in data by NPISH was $552 billion. The largest dollar investments were made in Health Care and Social Assistance ($329 billion), which is fourth largest when compared with the business sector. The second largest dollar investments by NPISH were made in Educational Services ($149 billion).

6 Conclusions

In this paper, we 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. In our experimental estimates, we find 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, which yields an average annual growth of 4.2 percent. Cumulative current-dollar investment for the period 2002–2021 was $2.6 trillion. Overall, our results indicate that business sector investment in own-account data grew moderately faster than other business sector economic activity and slower than business sector investment in software.

The method we use in the paper augments the traditional sum-of-costs methodology for measuring other own-account intellectual property products in national economic accounts

by proxying occupation-level time-use factors using a machine learning model and the text of online job advertisements (Blackburn 2021). The method appears to be a feasible method for identifying occupations engaged in data-related activities and for estimating the time-effort that occupations allocate to data-related activities. The time-use factors we develop for occupations engaged in own-account data appear to have some overlap with the time-use factors we develop for occupations engaged in own-account software, which suggests an incentive to jointly estimate own-account data and own-account software to ensure consistency and prevent double counting if the scope of own-account software is expanded to include more occupations in the future.

In the future, we plan to expand the scope of estimation to include the NPISH and government sectors. In addition, this paper focuses on estimating current-dollar values and uses the depreciation rate for BEA's measures of own-account software as a proxy to calculate net stocks. Thus, important areas of development in the future will be a price index and depreciation rate specific to own-account data. Likewise, an important area for further development will be estimates of purchased data assets and more precise adjustments for data output used in capital formation.

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