Early Estimates of the Impact of AI Within BEA's Industry Economic Accounts

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Abstract Currently, there is not a line item in the U.S. national accounts that can be used to identify and measure the economic impact of artificial intelligence (AI). Therefore, we use tools to indirectly estimate the impact of AI via the lens of BEA's industry accounts. Throughout, we discuss important economic measurement challenges and make recommendations for next steps. Our baseline model finds evidence that AI is productivity enhancing and input saving and that AI is associated with a shift toward younger, relatively less educated workers. However, an alternative specification that makes different choices about the timing of the pervasiveness of AI yields less robust results, though it also suggests that AI is labor saving. Our findings highlight the importance of additional research and progress on economic measurement related to AI.

Keywords Artificial intelligence (AI), productivity, U.S. workforce, U.S. economic growth

JEL Code O4, O3, E01

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1. Introduction

It took about 13 years between the time that Robert Solow quipped about the information technology (IT) productivity paradox and a consensus emerged about the significant contribution of IT production, investment, and productivity to U.S. economic growth. Solow made the remark in 1987, and by the early 2000s, there were influential research papers that combined the latest (at the time) official economic data with sophisticated approaches to economic measurement to identify the direct contribution of IT to economic growth, and also analyzed potential macroeconomic "spillovers" and network effects between the use of IT and productivity growth. The consensus that emerged was that IT production was the dominant source of total factor productivity (TFP) growth in the mid 1990s and early 2000s and that production and investment in IT assets accounted for over a quarter of U.S. economic growth over this period, but that there was limited evidence of IT spillovers.[2]

Between 1987 and 2000, there were also important updates, improvements, and research into the official economic data that were critical for analyzing the economic impact of IT. In particular, in January 1996, the U.S. Bureau of Economic Analysis (BEA) introduced "chain-type" quantity measures that capture substitution within bundles of outputs (which is critical for capturing the shift toward IT production and investment) and in 1999 BEA recognized computer software purchases and spending on own account as investment and a capital asset. Furthermore, Jorgenson [2001] argued that an inflection point in Moore's law was important for identifying the acceleration of production and investment in IT. Finally, the official U.S. Bureau of Labor Statistics (BLS) productivity data were updated and revised in the late 1990s to expand the use of hedonic prices for IT and to include measures of IT capital services. Thus, resolving the computer productivity puzzle involved a confluence of time passing so more data could be released, improved statistics, new research, and an acceleration in the actual production and use of IT in the U.S. economy.

The premise for this paper is to investigate questions similar to those that were debated around the computer productivity paradox but focused on AI and framed within the U.S. national accounts and weighted toward challenges around economic measurement. The big-picture economic question is whether the zeitgeist around AI has translated into measured macroeconomic statistics. If so, where and how would we expect to see those impacts and what are the current measurement challenges in identifying and measuring those impacts? If not, is it because the economic statistics are lacking? If they are lacking, is a paradigm shift in economic statistics required to capture these new technologies, or is a narrow focus on particular areas and data collection sufficient? We expect that this paper will also help advance the dialogue between stakeholders and the economic measurement community on how to view the economic

[2] Impactful papers that led to this consensus are Oliner and Sichel [2000], Jorgenson et al. [2000]. Jorgenson [2001] gives macroeconomic account of the sources of economic growth while Jorgenson and Stiroh [2000] gives an industry accounting. Stiroh [2002] found information and communications technology (ICT) investments were associated with labor productivity growth via the investment in assets but not with increases in total factor productivity growth.

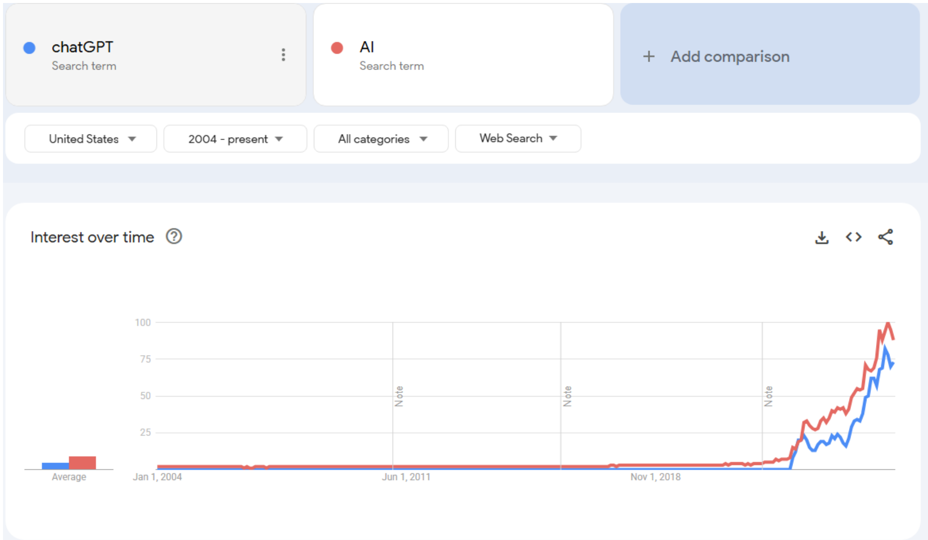

Figure 1. Google Trends of the search term chatGPT and AI from January 2004

impact of AI within the framework of the national accounts.

We lead by emphasizing that the need to be able to capture the economic impact of AI has been anticipated by the U.S. statistical system. The U.S. Census Bureau, along with the National Center for Science and Engineering Statistics, began collecting data on the use of AI by industry in the 2019 Annual Business Survey, with early data reported on AI use by business between 2016 and 2018. These early efforts demonstrate the forethought by statistical agencies to try to get ahead of the potential changes that AI could have on the economy and economic measurement. More broadly, general interest in AI did not occur until mid to late 2022. Figure 1 shows Google Trends interest over time in chatGPT and AI. While this is not definitive, for the remainder of the paper, we take 2022 as the year that AI entered the zeitgeist and a starting point for when AI could start to have macroeconomic impacts.

We also emphasize that we do not purport to be able to answer all of the initial questions that we have posed to motivate this paper. Our aim is to assess the current state of measuring the impact of AI based on available macro-oriented economic statistics within BEA's current economic accounts, draw some early inferences, and make recommendations for next steps. We do not focus on the microeconomic impacts of AI that may be prevalent well before impacts could be measured in the macro economy.

Based on a difference-in-difference model applied to BEA's economic data on the sources of economic growth, our baseline model finds significant interactions between the intensity of AI use and economic growth and the labor market. The model estimates that AI is productivity enhancing and input saving and that AI is associated with a shift toward younger, relatively less educated workers. An alternative model that makes different choices about the timing of the pervasiveness of AI does not show as strong results but does estimate that AI is labor saving. Additional research is required to focus on the sensitivity of the results to various issues.

The remainder of the paper proceeds as follows. In section 2, we overview where this paper fits in the burgeoning literature on the economic impact of AI. Section 3 describes the data we use to investigate where AI may be having measurable economic impacts within BEA's industry accounts. Section 4 provides basic summary statistics for the data, while section 5 presents the preliminary results. Finally, section 6 provides our early conclusions, next steps, and recommendations for advancing economic measurement of AI.

2. Where This Paper Fits

We reiterate that our objective is to examine the economic impact of AI using the (potentially narrow) lens of official economic statistics that are currently available to BEA. The premise of this approach is that if AI is a transformative technology, its impact should be evident in BEA's economic accounts.

A secondary purpose of this approach is that it allows us to examine what statistics are currently available within BEA's suite of economics statistics and potential areas where those statistics may need to be expanded to more accurately link changes in AI technology and its adoption to macroeconomic outcomes.

Thus, our paper complements the burgeoning literature that seeks to estimate the impact of AI across the U.S. economy. The papers are numerous and growing; so, given our specific purpose, we do not attempt to cite all of the numerous related papers. A few papers that are closely connected to our interest at the intersection of macroeconomic measurement and AI impacts are: Gazzani and Natoli [2024], Acemoglu et al. [2022], Filippucci et al. [2024], and Johnston and Makridis [2025]. Gazzani and Natoli [2024] examines macroeconomic impacts of AI using patents and finds positive responses of employment, wages, and (lagged) TFP to investments in AI. Our research differs in focus, by examining the impact of AI within BEA's economic accounts, and in approach as well. Second, Acemoglu et al. [2022] makes use of some of the same survey data that we rely on to construct our measures of AI intensity but focuses on modeling and estimating micro-level impacts of AI. Filippucci et al. [2024] discusses many of the ways and mechanisms that AI could impact an economy but does not attempt to estimate these relationships. In the paper most similar to ours, Johnston and Makridis [2025] relates AI exposure to labor market outcomes using difference-in-difference regressions. The authors find that AI is associated with employment and wage gains for AI-related workers, driven in part by gains for more educated and younger workers. Broadly, our interest and approach is similar, but the details of our implementation, data, and findings are substantively different. For example, our AI-intensity indicator is based on Census survey data, and our examination of the labor market is based on relative growth rates (which may be more closely tied to patterns of substitution and complementarity). Furthermore, we expand our focus to "outcome" variables that are outside of the labor market, like capital accumulation and productivity; on the other hand, we do not make use of the state-level variation that Johnston and Makridis [2025] incorporates.

Overall, the current literature is inconclusive about the broad impacts of AI. Thus, we view our paper as an addition to the discussion about datasets and approaches that are useful to tease out how AI is impacting the U.S. economy, with a special focus on how this relates to data published and used by BEA.

3. Data

3.1. AI-Intensity Measures Using Census Surveys

To measure AI intensity by industry, we use data from the 2019, 2022, and 2023 Annual Business Survey (ABS) and the 2023 Business Trends and Outlook Survey (BTOS). The Census Bureau conducts the ABS jointly with the National Science Foundation's National Center for Science and Engineering Statistics, sampling around 230,000 employer businesses each year US Census Bureau [2025a]. Questions about innovation in the ABS typically cover the prior 3-year period, so the 2019 survey reflects data for 2016–2018 and the 2023 survey reflects data for 2020–2022. For ease of reporting, we only refer to the final year in the 3-year span, meaning references to AI intensity in 2018 reflect the 2016–2018 period. Unlike the 2019 and 2023 ABS, the 2022 survey question about AI use reflects only the year 2021. Data on AI intensity for 2023 were not available from the ABS at the time of this analysis, so we use the 2023 BTOS instead. The BTOS is another Census survey developed in 2022 to address the significant lag in other surveys by reporting "near real-time" data on a variety of business conditions that occurred in the previous 2 weeks, including use of AI US Census Bureau [2025b].

The extent to which a company used AI in its production process was captured differently in each survey. In the 2019 ABS, companies chose from six options: Did not use; Tested, but not used in production or service; Low use; Moderate use; High use; and Don't know. The 2022 ABS had four options: A lot, Somewhat, A little, and Not at all. The 2023 ABS had five options: This technology is not applicable to this business; Applicable, but did not test or use; Tested, but did not use as part of the processes or methods; Used as part of the processes or methods; and Don't know. The 2023 BTOS provided three options: Yes, No, and Do not know. To account for the variability across years, we create a binary indicator of AI use that represents any positive indication of AI usage during the survey period. This means if AI was tested but not used in production, it is counted as AI use. This also means that survey responses of "Unknown" and its equivalent are not counted as using AI.

How AI is defined also varies somewhat across the surveys. The 2019 and 2023 ABS have the same definition: "Artificial intelligence is a branch of computer science and engineering devoted to making machines intelligent. Intelligence is that quality that enables an entity to perceive, analyze, determine response and act appropriately in its environment." For respondents that take the time to read the full definitions at the end of the survey, the definition is expanded to include examples:

> "Systems with artificial intelligence perform functions including, but not limited to, speech recognition, machine vision, or machine learning:
>
> - Speech recognition transforms human speech into a format useful for computer applications (for example, a digital assistant)
> - Machine vision uses sensors and software that allow images to be used as an input for computer applications (for example, systems that sort or inspect objects or support navigation in mobile equipment)
> - Machine learning uses statistical software and data to "learn" and make better predictions without reprogramming (for example, recommended systems for websites, or sales and demand forecasting)
>
> Artificial Intelligence technologies also include virtual agents, deep learning platforms, decision management systems, biometrics, text analytics, and natural language generation and processing."[3]

The 2022 ABS does not provide an explicit definition; instead, examples are provided: "Artificial intelligence (e.g., machine learning, planning, reasoning, and decision making)." The 2023 BTOS definition is different from the 2019 and 2023 ABS but uses much of the same language: "AI Definition: Computer systems and software that are able to perform tasks normally requiring human intelligence, such as decision-making, visual perception, speech recognition, and language processing. Types or applications of AI include machine learning, natural language processing, virtual agents, predictive analytics, machine vision, voice recognition, decision making systems, data analytics, image processing, etc."[4]

Each of the surveys are published by North American Industry Classification System (NAICS) industry, typically at the 2-digit or sector level, but sometimes at a more disaggregated level. For example, the 2023 ABS provides information for the overall information sector (NAICS 51) and for selected underlying subsectors: publishing (NAICS 511), telecommunications (NAICS 517), and data processing, hosting, and related services (NAICS 518). We conduct our analysis at the 2-digit NAICS or sector level because underlying industry detail is not consistently available.

[3] https://wayback.archive-it.org/5902/20231214231246/https://www.nsf.gov/statistics/srvyabs/surveys/srvyabs-2019-abs-1.pdf

[4] https://www2.census.gov/data/experimental-data-products/business-trends-and-outlook-survey/questionnaire-ai-supplement.pdf

AI use by industry is divided into quartiles to represent intensity in each year. We consider industries in the 4th quartile to be high-use or AI intensive.

3.2. BEA Industry Data on the Labor Market and Sources of U.S. Economic Growth

The starting point for our analysis is the AI Action Plan, which prompts the U.S. statistical system to study the impact of AI with a spotlight on the labor market impacts of AI. BLS is the primary producer and disseminator of official labor market data in the United States, but for the purpose of this paper, we focus on potentially relevant data that BEA assembles (jointly with BLS) within the BEA-BLS Integrated Industry-Level Production Account (ILPA). This dataset presents the sources of growth, bottom up, from the industry level and includes adjustments for labor and capital composition changes over time. The labor composition adjustment requires workers, their hours, and their compensation cross-classified by industry, age group, and educational attainment group, and these are the classifications we make use of in our analysis. We motivate these groupings with questions like: is the use of AI differentially related to changing employment of older workers (who may not be as AI-ready) relative to younger workers? And, is there any association related to wages for these groups; for example if relatively young workers are in demand due to their experience working with AI relative to older workers, this may be reflected in relative compensation. We have posed similar questions related to educational attainment; has AI interacted with relative demand for workers by broad level of educational attainment?

We expand from the labor market data mentioned above to explore the impact of AI at the industry level in the United States. The dataset for this is the BEA-BLS ILPA, which was mentioned above as the source for the labor market data. This dataset is updated annually by both agencies with a stated purpose that "allows analysts to trace aggregate GDP growth from its industry origins to changes in factors of production, including capital, labor, intermediate inputs, and (integrated) total factor productivity."[5] For the analysis in this paper, we use industry-level contributions to industry real output growth, including the contributions of capital by major asset grouping; labor by workers with a college degree or above and other workers; intermediate inputs by energy, materials, and services; and productivity growth by industry. Within the literature, these are sometimes referred to as "KLEMS" datasets. For the purposes in this paper, we view these data as being within the national accounts even though the ILPA data are a separate BEA-BLS data product that is not the source of the published BEA GDP-by-industry data. The key feature of these data is that they show the sources of real industry output growth. As described below, a main interest of this paper is to analyze how AI may or may not interact with the driving forces of economic growth.

Importantly, the ILPA provides the growth accounting where many of the challenges around measuring AI would manifest. Many of these are discussed in Highfill et al. [2025]. For example, identifying in which establishments and industries AI production takes place, measuring the use of AI by businesses

[5] https://www.bea.gov/data/special-topics/integrated-industry-level-production-account-klems

(which may be provided for free or bundled with other purchased products), measuring the unique inputs (such as data centers) that are used to produce AI, and measuring constant quality prices for AI services are important measurement challenges. When outputs or inputs in constant quality units are either mismeasured or not measured, this shows up in the residual TFP growth by industry in the ILPA.

4. Summary Statistics

In this section, we give a quick overview of the statistics we use and their evolution over the period that our dataset covers. We start with a summary of the AI-intensity measures calculated from the Census ABS and BTOS. Table 1 shows the average use of AI by private companies for 2018, 2021, 2022, and 2023. The data show use of AI in the production process was 3.4 percent in 2018, rose to 5.2 percent in 2022, and dropped to 4.4 percent in 2023. The last column of table 1 shows that uncertainty over AI use rose substantially by 2022 when 24.6 percent of companies reported not knowing if AI was used, up from 6.7 percent in 2018.

Table 2 shows the NAICS sectors in the lowest and highest quartiles for 2018 and 2022. Four sectors were in the highest quartile (i.e., were considered AI intensive) in both years: 51-information, 53-real estate and rental and leasing, 54-professional, scientific, and technical services, and 55-management of companies and enterprises. Sector 52-finance and insurance was AI intensive in 2018 but not in 2022, whereas sector 61-educational services was AI intensive in 2022 but not in 2018. While sectors in the highest quartile were mostly static over the period, sectors in the lowest quartile were more likely to fluctuate. Only three sectors were in the lowest quartile for both years, 11-agriculture, forestry, fishing, and hunting; 21-mining, extraction, and support activities; and 23-construction. Additionally, the distribution became more spread out between 2018 and 2022. While the 25th quartile value was relatively similar for 2018 (2.0 percent) and 2022 (2.1 percent), the 75th quartile value almost doubled, from 3.8 percent to 7.1 percent.

Next, we discuss the variables that are published within the BEA-BLS Integrated Industry-Level Production Account as mentioned above, augmented to include tabulations from the underlying labor database within that account. From these datasets, we gather 38 potential industry-level impact variables that we study relative to AI intensity.

Table 3 presents summary statistics for our 38 variables of interest and splits the sample averages across the four scenarios that we use in our baseline difference-in-difference regressions: the industry mean growth rate (or contribution) through 2021 for non-AI intensive industries, the mean growth rate through 2021 for AI-intensive industries, and growth rates for 2021–2023 for those same groups.[6] These summary statistics and our regressions cover only the private economy; that is, we drop the government

[6] I.e., growth rates are for years 1998-2021 and 2022-2023.

sector from our analysis, in part because the AI use variables are not available for the federal or state and local sectors. We do not provide exposition on each of these 38 variables but highlight that TFP and average labor productivity (ALP) growth for the AI-intensive industries were much stronger than that of non-AI intensive industries after 2021. A main motivation for the regression results presented in the next section is to test whether the differences presented in this table are statistically significant, but we have included the basic summary data table to give a sense of how the averages of these variables have changed over time and relate to AI intensity.

5. Preliminary Estimates of AI Impacts Using Difference-in-difference

Based on our discussion above, our baseline investigation into the relationship between AI use and industry-level dynamics involves two basic choices: (1) how to define intensity of AI use and (2) at which point in the time series shall we test for the relationship between AI and the variable of interest. For our preliminary analysis, we define relatively high AI use based on the top quartile of AI use in 2022. As noted in Stiroh [2002], this produces a relative impact analysis; that is, we do not investigate whether AI use is directly related to productivity, for example, but investigate whether relatively intensive AI use is related to relative differences in productivity growth. Another way to frame this is that any macro changes, like business cycles, are assumed to not impact AI-intensive and non-AI-intensive industries differentially; therefore, any observed differences, after controlling for pre-2022 trends, can be parsed out as being related to the relative intensity of AI use (because other factors impact industries the same way).

Before discussing the regression results, we note that our indicator of AI intensity is available *based on currently available data* for only 19 private-sector industries, while our industry outcome variable is available for 61 private sector industries. That is, we are interested in a basic relationship of the form:

$$y_{it} = \alpha_i + \gamma_t + \beta(D_s \times Post_t) + \epsilon_{it}$$

where y_{it} is one of industry-level variables for the 61 private sector industries, α_i is an industry-level fixed effect, γ_t is a year effect, and the interaction of interest is the coefficient on the $(D_s \times Post_t)$ variable which is the interaction of the AI-intensity indicator at the 19 sector level and the 2022 and 2023 year indicator. We use the estimation strategy in Borusyak et al. [2024] to circumvent some of the challenges of off-the-shelf OLS; one particular advantage of the Borusyak et al. [2024] method is that it uses an imputation method to predict the trend in variables and then tests how AI intensity impacts that trend. Standard errors are clustered at the 19 sector level to correspond to the AI-intensity measures.

Another complication that we note is the potential overlap between AI users and AI producers. Stiroh [2002] intentionally separated users of information technology from producers to avoid confounding broader impacts of IT with narrow impacts driven solely by grouping IT producers with those that use IT. At this stage in the development of data related to measuring AI, separating producers of AI from users AI is even more complicated than separating producers of IT technology in the 2000s from users of IT technology because even the main producers of core AI-technology often produce other products or services (that at some point may have been or still may be the primary output). Thus, for this exploratory work, we do not attempt to separate AI producers from AI users; in essence this assumes that the AI use effect dominates the AI production effect for the set of industries that do both.

The relationship between AI intensity and the sources of economic growth is theoretically ambiguous, especially in the shorter run. For example, AI use could be either input using or input saving. AI has been noted as being a significant draw on energy, for example O'Donnel and Crownhart [2025]. Thus, relative intensity of AI use may be associated with an increase in energy use. On the other hand, AI could lead to a reduction in purchases of intermediate services and could be labor saving. It could also be the case that employing AI requires additional resources and therefore could require more inputs to produce the same level of output. And of course, AI may have no measurable impact or impacts that go in opposite direction but cancel out at the level of detail that our current measurement permits.

The results of our baseline specification of the impact of AI after 2021 are in Table 4.

5.1. AI Intensity and the Labor Market

We start by describing the relationship between AI and the labor market, as that is the focus of the AI Action Plan. The labor market related variables are (3)–(18) in the table. Our first set of labor market variables are related to the age of the workforce across industries, rows (3)–(10), and the fundamental question is whether AI use impacts the workforce differentially. Theory does not give a strong prediction here. For example, AI could increase demand for older workers if a more experienced workforce is needed to manage relatively fewer and younger workers. Or, relatively older workers may not have the pertinent skills to work with an AI-intensive workforce, and thus AI could be associated with a decrease in demand for older, more experienced workers. Once again, a cutoff is put in place to define where these tradeoffs may be happening at the margin. We define mid-late career workers as those over 45 to examine how AI is related to changes in that group of workers, with the basic idea being that those over 45 would have limited institutional educational experience related to learning and training in the use of AI. Second, we define the baseline as early-mid career workers aged 25–44 as those who may be trained in AI and are more likely to use AI in their regular job responsibilities. Finally, workers less than 25 are put in a group of young workers who are most likely entry-level workers whose tasks may be impacted by AI. AI may increase the (relative) demand for these very young workers if, as a result of AI, entry-level workers can now complete tasks that historically take more experience, but it could decrease the demand if no workers need to replace these tasks.

Our results indicate that, at the level of detail we analyze, that there are no significant impacts of AI on the gap between mid-late career workers and early-mid career workers. That is, the growth rates of employment, hours, compensation per hour, and hours per worker is not significantly different in industries that are relatively intensive in AI use. On the younger end of the age distribution, our results indicate that the employment and hours of the youngest group of workers increased relative to early-mid career workers in industries that are relatively AI intensive. To be clear, we do not take this as conclusive evidence that AI has increased the demand for very young workers but point this out as being worthy of additional study. It is noteworthy that even though the work performed by very young workers relative to the middle group of workers increased in AI-intensive industries, the compensation per hour declined relative to early-mid career workers in this same set of industries.

Our next set of results focuses on the relationship between AI and educational attainment, rows (11)–(18). Our baseline is workers with a bachelor's degree and we test the relationship between AI and those workers relative to other levels of educational attainment. First, the results show that employment and hours for workers with less than a college degree increased relative to BA workers (rows(11) and (12)) in AI intensive industries even though compensation per hour declined for the same set of workers. The model results do not show any significant differences between workers with a BA degree and those with a higher level of educational attainment related to AI intensity.

5.2. AI Intensity and the Sources of Growth

Next, we turn our attention to how AI is related to the industry-level sources of economic growth. Rows (1) and (2) show the estimated relationship between AI intensity and total factor productivity and average labor productivity growth, respectively. Under our baseline specification, AI intensity is associated with significantly higher TFP after 2021, and labor productivity is also estimated to be higher, but not at the same level of statistical significance. This result can be seen in the interaction terms in Table 4. For example, the coefficient for the interaction term between AI intensity and the Post variable indicate that after controlling for industry and year effects, industries in the high AI-intensity group experienced TFP growth higher by about 2 percent per year and ALP higher by about 1 percent per year. The econometric specification estimates that the TFP result is statistically significant at the 1 percent level and the ALP result is significant at the 10 percent level. Importantly, unlike a hedonic regression that attempts to measure the marginal impact of a characteristic on price change, the estimates in this table do not give the marginal impact of AI; that is, the approach does not estimate the extra productivity growth that is associated with an increase in AI use; it merely parses out the association between being in the high AI grouping and compares that across the less AI-intensive group.

While this is just a single model estimate, if true, the interpretation of this is that industries that are able to effectively make use of AI also experienced boosted productivity growth. With respect to the TFP measure, one interpretation of this is that holding the level of inputs fixed, AI industries are able to produce more output without employing additional inputs. An interpretation of the relatively higher average labor productivity growth for AI intensive industries is that AI is associated with an increase in capital deepening, labor composition, or TFP that enables workers in these industries to be relatively more productive.[7]

Rows (19)–(23) show the relationship between AI intensity and the industry level sources of economic growth based on the baseline model. According to this model, there is a statistically significant relationship between AI and the contributions of labor input and intermediate input but not total capital input or the overall growth of gross output at the industry level. The results indicate that AI intensity is negatively correlated with the contributions of both college and non-college labor; that is, relatively high AI intensity is associated with relatively lower contributions of both types of labor. This is consistent with the basic idea that AI is labor saving, with the important caveat this is only one specification and not necessarily robust to many of the challenges and specification choices that we have described earlier. The results also show that relatively intensive users of AI use less intermediate inputs, and this appears to be driven by intermediate inputs of services as shown in row (37). Finally, while the overall relationship between AI and the use of capital input is not statistically significant, at the level of the assets tracked in the ILPA, the results indicate that users of AI employ less ICT related capital inputs and structures, land, and inventories. While the result that AI is associated with less IT is a bit of a puzzle, if AI, in general, allows producers to economize on all inputs, this particular result may not be out of the realm of possibility.

Overall, our baseline specification indicates that AI intensity appears to be input saving, and productivity enhancing in the macro economy. In the next section, we explore how the results change under an alternative specification and leave a more complete set of robustness checks to future research.

5.3. Alternative Specification

As noted earlier, there are many choices in how to define the variables we have used to form our baseline. Given the enormous interest in how AI interacts with the rest of the economy, our baseline model makes defensible choices on model specification, and our primary objective is to begin exploring these economic relationships. We also want to present at least one alternative specification that explores how results change with different analyst choices. The alternative we explore is a definition of AI intensity based on AI intensity in 2018 (instead of the baseline of 2022). One way to think about this is that this exercise looks a definition of AI use based on relatively early adopters.

The results in Table 5 show that there are some differences in model results between the specifications but some similarities as well. The similarities are concentrated on the interaction between AI intensity

[7] Labor productivity growth is the sum of TFP growth and the share weighted growth rates of capital deepening and labor quality growth.

and the labor market. This version of the model also estimates that AI is labor saving; that is, increased AI use is associated with a decline in the contribution of labor input relative to other, less AI-intensive industries. Within the labor market, this model estimates that college-educated labor declined relative to workers without any college in AI-intensive sectors, as in our baseline model, but again we caution against interpreting this as strong evidence of change in the demand for college degrees as a result of AI. Most of the other results differ from our baseline, although the sign of the relationship between AI and the productivity variables is the same, neither relationship is estimated to be statistically significant.

6. Conclusions, Next Steps, and Recommendations

The late 1990s and early 2000s established "economics on internet time" Jorgenson et al. [2005]. Computing power and ease of access to data via the internet accelerated and with this came important advances in economic research. Unlike the ICT revolution and the onset of the information age, *use* of AI technology is not necessarily associated with the same large capital investments that *users* of ICT had to undertake. Thus, tracing the macro economic impact of AI has a different set of challenges, even though the *production* of AI and the *production* of ICT both required significant economic investment. Thus, in this paper, we have examined the ongoing relationship between AI and the macro economy by estimating early impacts on the sources of economic growth and the labor market using currently available data within BEA's industry economic accounts indirectly. That is, we have not directly measured the use of AI, how many dollars are spent on it, or how its quality has changed over time in an attempt to directly measure its contribution to growth like any other input in the economy. But we have tried to look at this indirectly to assess where in the economy relative AI intensity is associated with differences in the driving forces of economic growth.

In our baseline model, we find that AI intensity is associated with saving on inputs (including labor) and increased productivity. With respect to the labor market, the models estimate some differential impacts with respect to the age and educational attainment of the workforce. These results are sensitive to the model specification in terms of the choice of year for defining AI intensity, but even our alternative version of the model indicates AI is associated with savings on the use of labor.

Our final statement on the results presented in this paper is that they are preliminary and have not undergone an extensive set of robustness checks, like sensitivity to choice of the AI-intensity indicator and which year to choose for that indicator, how to weight the industries (at this point there is no weighting) and which years to choose as the starting year that AI may have measurable industry-level impacts (we chose 2022). Nevertheless, given the huge demand for analysis on how AI is impacting the U.S. economy, we have undertaken this preliminary research.

The next steps for this paper are plentiful, including the basic robustness checks noted earlier, moving on to more direct measures of AI and its use in production, and econometric-based estimates of how the use of AI is related to other inputs used in production. This would require substantial progress in economic measurement, and thus we end this conclusion with some recommendations that could help the economic measurement community advance toward that goal.

Our first three recommendations relate specifically to Census surveys, starting with increasing the level of industry detail across all sectors to allow for a finer assignment of AI intensive industries. Second, we recommend keeping the surveys consistent each year to allow for enhanced time series analysis. This relates not only to the definition used to describe AI, but also for the survey response options. For example, some of the Census surveys provided an indication of whether AI was used a lot or a little, but we could not incorporate this nuance into our analysis because these variables were not consistently collected across all years. Relatedly, to the extent that it's possible, the significant increase in survey respondents indicating they do not know if AI is used in the production process should be addressed. One possibility is to not give respondents that option, as was the case in the 2022 ABS. Our last recommendation is relevant to the broader economic measurement community, and that is to develop clear and implementable definitions to separate the various components in the production of AI from the use of AI. This is necessary for attributing the impacts of AI to the appropriate economic mechanisms.

Table 1. Use of AI to Produce Goods and Services by Private Companies			
Year	**Used AI**	**Did not use AI**	**Don't know if AI used**
2018	3.4	89.9	6.7
2021	4.8	95.2	-
2022	5.2	70.2	24.6
2023	4.4	81.2	14.4

Source: Authors' calculations based on the 2019, 2022, and 2023 Annual Business Survey and the 2023 Business Trends and Outlook Survey.

Table 2. AI Intensity by Sector for 2018 and 2022			
AI Intensity	**2018 and 2022**	**2018 only**	**2022 only**
Lowest quartile	11-Agriculture, forestry, fishing, and hunting	71-Arts, entertainment, and recreation	48-49-Transportation and warehousing
	21-Mining, extraction, and support activities	81-Other services	72-Accommodation and food services
	23-Construction		
Highest quartile (i.e., AI intensive)	51-Information	52-Finance and insurance	61-Educational services
	53-Real estate and rental and leasing		
	54-Professional, scientific, and technical services		
	55-Management of companies and enterprises		

Notes: The 25th quartile value of AI use was 2.0% in 2018 and 2.1% in 2022. The 75th quartile value was 3.8% in 2018 and 7.1% in 2022.

Source: Authors' calculations based on the 2019 and 2023 Annual Business Survey.

Table 3: Summary Statistics and AI Intensity

	Full Sample	NonAI Through 2021	AI Through 2021	NonAI 2021-2023	AI 2021-2023
	mean	mean	mean	mean	mean
TFP	0.483	0.472	0.747	-0.411	2.01
ALP	1.467	1.241	2.912	0.02	2.991
Gross Output	1.687	0.998	4.033	2.97	5.288
Employment EM/YW	-0.026	-0.277	1.947	-1.833	-1.771
Hours EM/YW	-0.828	-1.092	0.989	-2.03	-2.782
Compensation/Hr EM/YW	-0.226	-0.215	-0.133	-0.82	0.745
Hours per worker EM/YW	-0.803	-0.815	-0.958	-0.197	-1.011
Employment ML/EM	-1.953	-2.226	-1.96	0.768	0.712
Hours ML/EM	-1.902	-2.183	-1.873	0.816	0.706
Compensation/Hr ML/EM	0.347	0.214	0.491	1.312	1.47
Hours per worker ML/EM	0.051	0.044	0.087	0.048	-0.006
Employment BA/noBA	2.539	2.504	3.383	1.133	0.73
Hours BA/noBA	2.189	2.176	3.102	0.444	-0.136
Compensation/Hr BA/noBA	0.318	0.409	0.678	-1.551	-0.478
Hours per worker BA/noBA	-0.35	-0.327	-0.28	-0.689	-0.866
Employment MA+/BA	-0.945	-1.046	-0.574	-0.87	-0.263
Hours MA+/BA	-0.769	-0.921	-0.27	-0.477	0.172
Compensation/Hr MA+/BA	0.549	0.534	0.262	1.321	1.295
Hours per worker MA+/BA	0.176	0.125	0.304	0.393	0.435
Software	0.101	0.057	0.287	0.082	0.36
R&D	0.066	0.047	0.132	0.095	0.201
Computers	0.063	0.041	0.186	0.005	0.07
IT Hardware	0.11	0.056	0.381	0.014	0.193
Total Capital	0.495	0.331	1.288	0.296	0.796
Communication Equipment	0.047	0.016	0.195	0.008	0.123
Instruments	0.009	0.007	0.02	0.01	0.008
Other Equipment	0.055	0.06	0.057	0.012	-0.025
Structures, Land, Inventories	0.096	0.072	0.205	0.087	0.106
Transportation Equip	0.041	0.031	0.116	-0.005	-0.082
Entertainment Originals	0.016	0	0.09	0.002	0.034
Intermediate Input	0.462	0.125	1.256	2.143	1.625
College Labor	0.299	0.177	0.745	0.507	0.676
Non College Labor	-0.052	-0.107	-0.003	0.435	0.18
Total Labor	0.247	0.069	0.742	0.942	0.856
Energy Intermediates	-0.041	-0.065	0.013	0.096	-0.012
Services Intermediates	0.597	0.35	1.107	1.975	1.672
Materials Intermediates	-0.094	-0.16	0.136	0.071	-0.035
Other Capital	0.202	0.171	0.397	0.103	0.008
Observations	1586	1200	264	100	22

EM workers are Early-Mid Career Workers (25-44); YW are Young Workers less than 25; ML workers are Mid-Late career workers 45+
BA workers are those with a Bachelor's degree; noBA workers are those without a Bachelor's; MA+ workers are those with an MA degree or PhD

Table 4: Regression Results related to AI Intensity

	VARIABLES	Interaction Term	SE	Constant	SE	R-squared
(1)	TFP	2.146***	(0.599)	0.454***	(0.00831)	0.092
(2)	ALP	1.300*	(0.700)	1.449***	(0.00972)	0.159
(3)	Employment EM/YW	-2.163**	(0.981)	0.00425	(0.0136)	0.209
(4)	Hours EM/YW	-2.834**	(1.097)	-0.789***	(0.0152)	0.212
(5)	Compensation/Hr EM/YW	1.483**	(0.525)	-0.246***	(0.00729)	0.359
(6)	Hours per worker EM/YW	-0.671	(0.646)	-0.793***	(0.00896)	0.170
(7)	Employment ML/EM	-0.322	(0.524)	-1.948***	(0.00727)	0.422
(8)	Hours ML/EM	-0.419	(0.534)	-1.896***	(0.00740)	0.356
(9)	Compensation/Hr ML/EM	-0.119	(0.293)	0.348***	(0.00406)	0.229
(10)	Hours per worker ML/EM	-0.0968	(0.101)	0.0520***	(0.00140)	0.105
(11)	Employment BA/noBA	-1.282**	(0.499)	2.557***	(0.00692)	0.152
(12)	Hours BA/noBA	-1.506**	(0.642)	2.210***	(0.00890)	0.162
(13)	Compensation/Hr BA/noBA	0.804*	(0.402)	0.306***	(0.00558)	0.118
(14)	Hours per worker BA/noBA	-0.224	(0.261)	-0.347***	(0.00362)	0.222
(15)	Employment MA+/BA	0.135	(0.743)	-0.947***	(0.0103)	0.136
(16)	Hours MA+/BA	-0.00190	(0.787)	-0.769***	(0.0109)	0.130
(17)	Compensation/Hr MA+/BA	0.246	(0.511)	0.545***	(0.00708)	0.074
(18)	Hours per worker MA+/BA	-0.137	(0.263)	0.178***	(0.00364)	0.107
(19)	Gross Output	-0.717	(0.772)	1.697***	(0.0107)	0.324
(20)	Total Capital	-0.457	(0.374)	0.501***	(0.00519)	0.517
(21)	Total Labor	-0.758***	(0.242)	0.258***	(0.00336)	0.368
(22)	Intermediate Input	-1.649**	(0.585)	0.484***	(0.00811)	0.196
(23)	TFP	2.146***	(0.599)	0.454***	(0.00831)	0.092
(24)	Communication Equipment	-0.0642**	(0.0261)	0.0474***	(0.000362)	0.889
(25)	Computers	-0.0808*	(0.0388)	0.0642***	(0.000539)	0.362
(26)	Instruments	-0.0144	(0.0118)	0.00968***	(0.000163)	0.711
(27)	Other Equipment	-0.0339	(0.0771)	0.0558***	(0.00107)	0.373
(28)	Structures, Land, Inventories	-0.113**	(0.0408)	0.0974***	(0.000565)	0.282
(29)	Transportation Equip	-0.161	(0.182)	0.0435***	(0.00252)	0.359
(30)	College Labor	-0.399***	(0.137)	0.305***	(0.00190)	0.294
(31)	Energy Intermediates	-0.187	(0.158)	-0.0388***	(0.00220)	0.091
(32)	Entertainment Originals	-0.0580	(0.0426)	0.0166***	(0.000591)	0.770
(33)	IT Hardware	-0.145***	(0.0333)	0.112***	(0.000462)	0.608
(34)	Materials Intermediates	-0.402	(0.367)	-0.0884***	(0.00509)	0.216
(35)	Non College Labor	-0.359**	(0.137)	-0.0468***	(0.00191)	0.365
(36)	Other Capital	-0.322	(0.294)	0.206***	(0.00408)	0.340
(37)	Services Intermediates	-1.059**	(0.504)	0.612***	(0.00699)	0.120
(38)	R&D	0.0205	(0.0269)	0.0661***	(0.000373)	0.774
(39)	Software	0.0477	(0.130)	0.100***	(0.00181)	0.706

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
n=1586

EM workers are Early-Mid Career Workers (25-44); YW are Young Workers less than 25; ML workers are Mid-Late career workers 45+
BA workers are those with a Bachelor's degree; noBA workers are those without a Bachelor's; MA+ workers are those with an MA degree or PhD

Table 5: Regression Results related to AI Intensity, Alternative Model

	VARIABLES	Interaction Term	SE	Constant	SE	R-squared
(1)	TFP	0.912	(0.987)	0.467***	(0.0174)	0.090
(2)	ALP	0.550	(0.590)	1.457***	(0.0104)	0.159
(3)	Employment EM/YW	-1.110	(1.128)	-0.00615	(0.0199)	0.208
(4)	Hours EM/YW	-1.149	(1.307)	-0.808***	(0.0231)	0.210
(5)	Compensation/Hr EM/YW	0.879	(0.649)	-0.241***	(0.0115)	0.358
(6)	Hours per worker EM/YW	-0.0387	(0.494)	-0.802***	(0.00873)	0.170
(7)	Employment ML/EM	-0.0133	(0.523)	-1.952***	(0.00923)	0.422
(8)	Hours ML/EM	-0.0461	(0.573)	-1.901***	(0.0101)	0.356
(9)	Compensation/Hr ML/EM	-0.118	(0.258)	0.349***	(0.00455)	0.229
(10)	Hours per worker ML/EM	-0.0328	(0.114)	0.0512***	(0.00202)	0.105
(11)	Employment BA/noBA	-1.788***	(0.579)	2.571***	(0.0102)	0.152
(12)	Hours BA/noBA	-1.806**	(0.635)	2.221***	(0.0112)	0.162
(13)	Compensation/Hr BA/noBA	1.464***	(0.494)	0.292***	(0.00871)	0.119
(14)	Hours per worker BA/noBA	-0.0183	(0.142)	-0.350***	(0.00250)	0.221
(15)	Employment MA+/BA	-0.0180	(0.738)	-0.945***	(0.0130)	0.136
(16)	Hours MA+/BA	-0.198	(0.777)	-0.766***	(0.0137)	0.130
(17)	Compensation/Hr MA+/BA	0.605	(0.474)	0.538***	(0.00837)	0.074
(18)	Hours per worker MA+/BA	-0.180	(0.214)	0.179***	(0.00379)	0.107
(19)	Gross Output	-1.391*	(0.684)	1.712***	(0.0121)	0.324
(20)	Total Capital	-0.421	(0.296)	0.502***	(0.00523)	0.517
(21)	Total Labor	-0.859***	(0.254)	0.263***	(0.00449)	0.369
(22)	Intermediate Input	-1.024	(0.894)	0.480***	(0.0158)	0.196
(23)	TFP	0.912	(0.987)	0.467***	(0.0174)	0.090
(24)	Communication Equipment	-0.0548**	(0.0252)	0.0475***	(0.000444)	0.889
(25)	Computers	-0.0977***	(0.0294)	0.0648***	(0.000520)	0.363
(26)	Instruments	-0.00454	(0.00983)	0.00956***	(0.000173)	0.710
(27)	Other Equipment	-0.00126	(0.0668)	0.0554***	(0.00118)	0.373
(28)	Structures, Land, Inventories	-0.103**	(0.0362)	0.0977***	(0.000639)	0.282
(29)	Transportation Equip	-0.229	(0.146)	0.0453***	(0.00257)	0.364
(30)	College Labor	-0.410***	(0.135)	0.306***	(0.00239)	0.294
(31)	Energy Intermediates	-0.205	(0.166)	-0.0378***	(0.00294)	0.091
(32)	Entertainment Originals	-0.0461	(0.0374)	0.0166***	(0.000661)	0.769
(33)	IT Hardware	-0.152***	(0.0257)	0.112***	(0.000454)	0.609
(34)	Materials Intermediates	-0.403	(0.382)	-0.0869***	(0.00675)	0.216
(35)	Non College Labor	-0.449***	(0.136)	-0.0438***	(0.00240)	0.366
(36)	Other Capital	-0.337	(0.232)	0.208***	(0.00410)	0.341
(37)	Services Intermediates	-0.415	(0.795)	0.604***	(0.0140)	0.119
(38)	R&D	0.0234	(0.0229)	0.0660***	(0.000403)	0.774
(39)	Software	0.0910	(0.100)	0.0996***	(0.00177)	0.706

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
n=1586

EM workers are Early-Mid Career Workers (25-44); YW are Young Workers less than 25; ML workers are Mid-Late career workers 45+
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