Telecom Advisory Services LLC

ECONOMIC IMPACT OF CLOUD COMPUTING AND **ARTIFICIAL INTELLIGENCE IN THE UNITED STATES**

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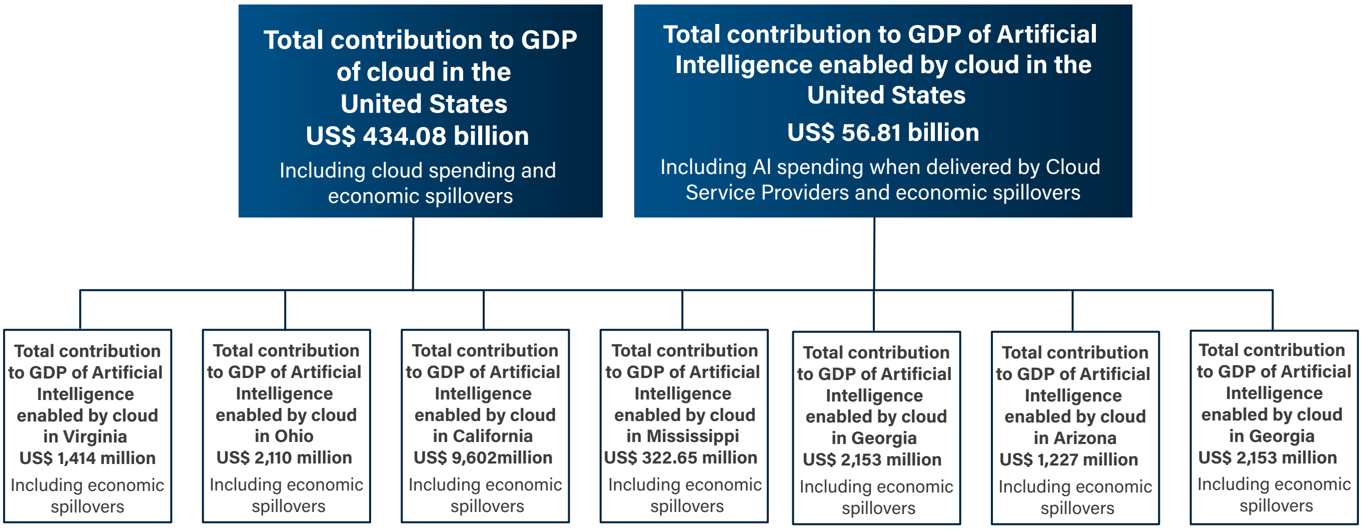

Source: Telecom Advisory Services analysis

Prior research on the macro-economic contribution of cloud computing has concluded that, driven by its impact on capital efficiency and stimulus of product development, cloud represents an engine of economic growth. That being said, beyond the economic impact of cloud itself, it is relevant to investigate whether there is additional value generated by cloud enabled artificial intelligence. The purpose of this study is to assess the economic contribution of cloud computing and evaluate the interaction benefits that arise as an enabler of AI in the United States.

The US is the most mature cloud computing market in the world, having reached US$ 361.94[1] billion in spending in 2023, representing 1.32% of its GDP. As in the case of cloud computing, AI spending in the US is the largest in the world, amounting to US$ 76.09 billion.[2] In particular, spending by US enterprises in purchasing AI technology from cloud service providers in the US for 2023 amounts to US$ 6.92 billion (or 9.09% of the total AI market) and has been growing at 42.87% per year.

Recognizing that the economic contribution of cloud and AI includes not only user spending, but also spillovers in terms of production efficiencies to the whole economy, total impact was estimated as follows:

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[1] *IDC. Semiannual Public Cloud Services Tracker (2024H1)*
[2] *IDC. Semiannual Artificial Intelligence Intrastructure Tracker (2023H2)*

- **The total GDP contribution of cloud in the US in 2022, comprising cloud spending and its spillovers on the economy, is sizable: US$ 404.59 billion. Our projections for 2023 and 2024 allow us to estimate a total GDP contribution of cloud computing increasing to US$ 434 and US$ 502 billion, respectively.**

- **The contribution to GDP derived from AI enabled by cloud amounted to US$ 69.86 billion in 2022.**

- **Over the next ten-year timeframe (2022-2031), the economic impact of cloud in the US is significant, reaching US$ 7.87 trillion (or 2.55% of the forecasted cumulative GDP for the same period), while the impact of AI as a technology enabled by cloud computing will reach US$ 1.19 trillion (or 0.39% of the forecasted cumulative GDP for the same period).**

On the basis of the estimates presented above, we estimated the differential economic impact across states and industries in the US

- **Cloud spillovers depend on AI usage intensity. More precisely, for the average State, an increase of 1% in cloud adoption yields a GDP increase of 0.115%. This is equivalent to US$ 807 million in Virginia, US$ 1 billion in Ohio, and US$ 4.6 billion in California.**

- **States that depict higher cloud adoption yield proportionally more economic gains from AI. For example, a state exhibiting 3.5% of enterprises having adopted AI combined with 30% of cloud adoption will benefit from 0.52% GDP increase, after increasing AI adoption by 1%. The GDP impact will increase to 0.58%, if cloud adoption is 50%. This additional effect generated by the increase in cloud adoption accounts to US$ 421 million in Virginia, US$ 544 million in Ohio, and US$ 2.4 billion in California.**

- **Accordingly, states which support a more pro-active approach to cloud development, are over performing in terms of economic impact of AI adoption.**

- **In some sectors, the main effects are linked to direct spending (professional activities, health, retail and wholesale trade, accommodation, and food), while in other sectors, the spillovers are the main source of economic impact. Likewise, the spillovers from cloud-enabled AI in some sectors are significant (financial services and insurance, real estate, manufacturing, information industry, utilities), while in others these AI-enhancing effects are negligible due largely to low levels of AI adoption (agriculture, arts and other services).**

Total contribution to GDP of Artificial Intelligence as complementary to cloud in the United States US$ 69.86 billion

Including AI spending when delivered by Cloud Service Providers and economic spillovers

Total contribution to GDP of Artificial Intelligence as complementary to cloud in Manufacturing US$ 7,180 million

Including economic spillovers
Virginia: US$ 176 million
Ohio: US$ 443 million
California: US$ 1,385 million
Mississippi: US$ 75 million
Indiana: US$ 220 million
Arizona: US$ 72 million
Georgia: US$ 257 million

Total contribution to GDP of Artificial Intelligence as complementary to cloud in Finance and insurance US$ 18,688 million

Including economic spillovers
Virginia: US$ 240 million
Ohio: US$ 689 million
California: US$ 2,474 million
Mississippi: US$ 83 million
Indiana: US$ 138 million
Arizona: US$ 419 million
Georgia: US$ 600 million

Total contribution to GDP of Artificial Intelligence as complementary to cloud in Information industry US$ 5,059 million

Including economic spillovers
Virginia: US$ 104 million
Ohio: US$ 73 million
California: US$ 1,369 million
Mississippi: US$ 12 million
Indiana: US$ 27 million
Arizona: US$ 59 million
Georgia: US$ 188 million

Total contribution to GDP of Artificial Intelligence as complementary to cloud in Transportation and storage US$ 1,808 million

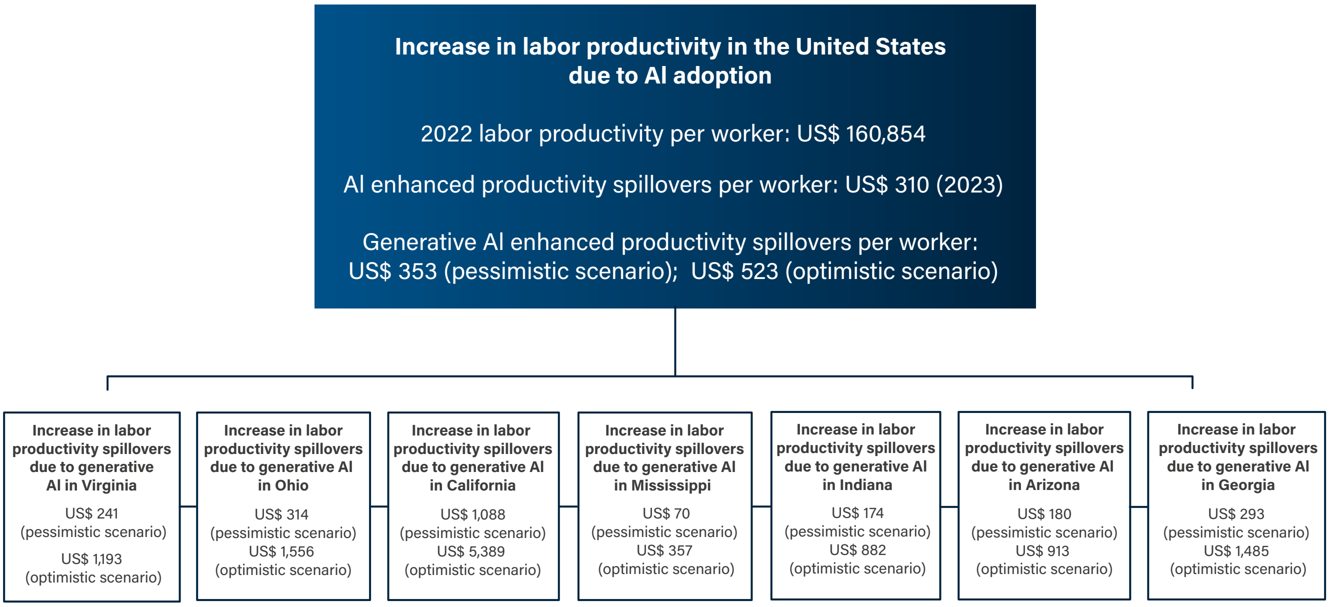
Including economic spillovers
Virginia: US$ 1 million
Ohio: US$ 2 million
California: US$ 186 million
Mississippi: US$ 10 million
Indiana: US$ 58 million
Arizona: US$ 53 million
Georgia: US$ 51 million

Source: Telecom Advisory Services analysis

The estimates of economic impact of cloud-enabled AI adoption presented above are mainly based on AI applications that precede generative AI. Since their launch at the end of 2022, generative AI models have moved from being "modular specialists" (generating images from captions, transcribing text to speech) to getting integrated into applications such writing assistance, coding, translation in multiple industries.

Most research conducted up to date on the economic impact of generative AI refers to its potential for enhancing productivity. By adjusting the productivity estimates calculated for 2022, generative AI has the potential to generate a boost in economic benefits.

- **Spillovers associated with cloud-AI complementarities varies depending on different scenario: In a pessimistic scenario, spillovers can potentially increase from US$ 310 to US$ 353 per worker as a result of generative AI (the increase is equivalent to US$ 241 million in Virginia, US$ 314 million in Ohio, and US$ 1 billion in California), and while in an optimistic scenario, from US$ 310 to US$ 523 dollars per worker (equivalent to US$ 1.1 billion in Virginia, US$ 1.5 billion in Ohio, and US$ 5.3 billion in California).**



Source: Telecom Advisory Services analysis

1. INTRODUCTION: THE COMPLEMENTARITY OF CLOUD COMPUTING AND ARTIFICIAL INTELLIGENCE (AI)

Deep economic transformations have been triggered by the development and diffusion of digital technologies over the past few decades, especially for businesses, where new procedures, reduced expenses, and improved operations have resulted in significant changes in production processes and operating models. These developments have made possible for organizations using information technology to improve their performance, which has, in turn, led to overall economic growth. While the contribution of the internet and broadband connectivity has been extensively researched in the empirical literature over the past twenty years, the analysis of the economic impact of more advanced and sophisticated digital tools is still evolving. Among the most recent technological innovations, cloud computing and AI are powerful tools for organizations looking to execute significant production model changes, accomplish their strategic goals, and remain competitive. In light of this, the purpose of this study is to complement the research on economic effects of digital technologies, focusing on cloud computing and evaluating the interaction effects that arise from complementing it with AI in the US.

Research on **the macro-economic contribution of cloud computing has concluded that, driven by its impact on capital efficiency and stimulus of product development, cloud represents an engine of economic growth.** The aggregated economic contribution of cloud to GDP is composed of: (i) the domestic revenues generated by cloud service providers and (ii) the spillover effects of cloud services on the total economy. The revenues represent the spending of public and private organizations purchasing cloud services[3] , while the spillover effects are the benefits generated by cloud computing in terms of IT cost efficiencies, new product development, support for incubation of startups and the like[4]. Furthermore, research has also shown that **the marginal economic impact of cloud adoption is greater for those geographies with higher cloud adoption rate.** If this is the case, it would be pertinent to investigate whether **the states of the US that have reached a higher cloud adoption rate depict a higher economic contribution of the technology: in other words, they should depict a higher return to scale.**[5]

Beyond the economic impact of cloud itself, it is also relevant to investigate whether there is additional value generated by the technology as an enabler to AI. Technological complementarity[6] is defined as technologies that work together to enhance or improve their respective overall performance or functionality.

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[3] The revenues are a measure of market demand that can be met through cloud providers based within the country or beyond the country's borders.

[4] For example, when cloud services enable the adoption of IT services in the SME sector, which benefits from the scalability of IT state-of-the-art, that is considered to be a spillover effect.

[5] Return to scale describes what happens to long-run returns as the scale of production increases, when all input levels including physical capital usage are variable. In the cloud case, as cloud adoption increases, the elasticity on GDP impact grows accordingly. See example for broadband in Katz, R., Jung, J. (2021). The economic impact of broadband and digitization through the COVID-19 pandemic: Econometric modelling. Geneva: International Telecommunication Union.

[6] As defined by Pattee (1978), Complementarity is defined as two components requiring "a separate mode of description that is formally incompatible with and irreducible to the other (but) where one mode of description alone does not provide comprehensive explanatory power".

The following study assesses a key dimension of complementarity examining the interrelationship between cloud and AI. AI is defined as the use of machine learning and related technologies that use data to train statistical models for the purpose of enabling computer systems to perform tasks normally associated with human intelligence or perception, such as computer visión, speech or natural language processing and content generation. This definition highlights that AI relies on data and other inputs to capture large volumes of information, perform analyses, and formulate outcomes. With its more recent advances, AI emerged as a transformative technology with the potential to reshape the economy and the society, revolutionizing the way we live and work. AI is becoming a driving force behind automation and innovation in various industries, offering immense opportunities while also raising unique challenges from the economics, legal and ethical perspectives.

On the other hand, AI requires an inordinate amount of computing resources to operate. In response to this requirement, cloud represents a powerful enabler. Furthermore, Big Data is expected to contribute to accelerate the use of Machine Learning, by providing useful information for AI-related decision-making processes. Under the premise of complementarity, it is reasonable to consider that AI adoption would be higher for enterprises that have adopted cloud and, consequently, business performance would be higher. Accordingly, we argue that **aggregate economic units (states or countries) with high adoption of cloud computing and AI will create high economic value, as measured by GDP contribution or productivity.**

This hypothesis can also be extrapolated to the new AI solutions of generative intelligence. One of the technology primary challenges of generative AI also remains computing resources (in this case, powerful GPUs, and large amounts of memory). Generative AI models (Large Language Models, Transformer-based models, ands adversarial networks) rely on neural networks to identify content patterns from large sets of data to generate new and original content or data. The recent class of generative AI models requires a ten to a hundred-fold increase in computing power to train models over the previous generation, depending on which model is involved. Thus, overall resource demand is roughly doubling about every six months. This represents a barrier to adoption by organizations seeking to implement in-house solutions. Beyond its development requirement, computing power is also required for training generative AI models, fine tuning them, and using them to provide responses to user prompts (while this last use requires less power per session, it involves many more sessions). This renders the cloud as an ideal solution to address the adoption challenge.

In sum, cloud computing and AI (moving from machine learning to generative AI) represent a classic case of technological complementarity. In this regard, the goal of this study is to examine the economic effects of cloud computing while also evaluating the interaction effects that arise from complementing it with AI and, in particular, generative AI in the US. For this purpose, we rely on the data provided by the Annual Business Survey (ABS) conducted by the US Census Bureau (USCB) and the National Center for Science and Engineering Statistics

(NCSES), which provides a unique opportunity as it provides data of cloud and AI adoption in enterprises across all states and economic sectors in the country.[7]

The study is structured as follows. In chapter 2, we present a brief description of the current state of adoption of cloud computing and AI in the US. Following this, chapter 3 introduces the theoretical model of an aggregate production function for our empirical analysis to estimate the economic growth of cloud and AI as a complementary technology. In chapter 4, we specify the econometric models to estimate the economic contribution of both technologies. In chapter 5, we present the estimates of economic contribution in the aggregate for the whole country and disaggregated for a subset of states for cloud computing and, then AI as a technology complementary with cloud. In chapter 6, we extrapolate the results of the analysis to address the economic impact of generative AI. Chapter 7 presents final conclusions and implications. The appendix reviews the state of the research literature regarding cloud computing and AI for economic growth and their potential complementarity examined to frame the study hypotheses.

[7] The ABS covers all nonfarm businesses filing Internal Revenue Service tax forms as individual proprietorships, partnerships, or any type of corporation, and with receipts of $1,000 or more with paid employees.

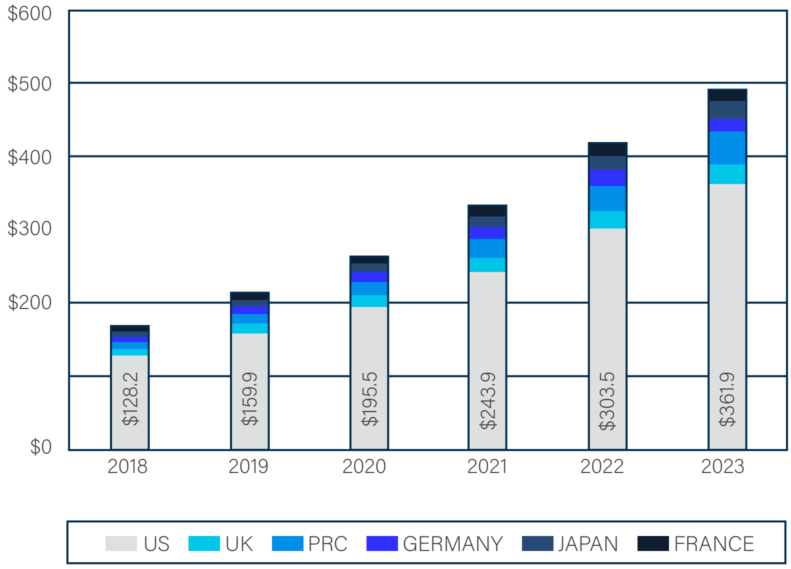
2. THE STATE OF DEVELOPMENT OF CLOUD COMPUTING AND AI IN THE UNITED STATES

Adoption and spending of cloud computing and AI in the US are the highest in the world. This section presents a general overview of adoption and spending by state and industries to set the stage for the analysis of their economic contribution.

2.1. CLOUD COMPUTING

The US is the most mature cloud computing market in the world, having reached US$ 361.9 billion in spending in 2023 (54.6% of the global demand of US$ 662.97 billion[8]) (see graphic 2-1).

Graphic 2-1. Selected Advanced Economies: Cloud computing constant vendor revenues (in billions US$) (2018-2023)



Note: AI Platforms excluded from vendor revenues
Source: IDC Semiannual Public Cloud Services Tracker (2023H1 Release)

This level of cloud spending represents 1.32% of 2023 GDP of the US.

As of 2018 (the last survey data was released in 2019), the Annual Business Survey of the US Census Bureau reported that cloud computing had been adopted by 34.61% of businesses.[9] A disaggregation of adoption by State indicates that fifteen states registered an adoption rate

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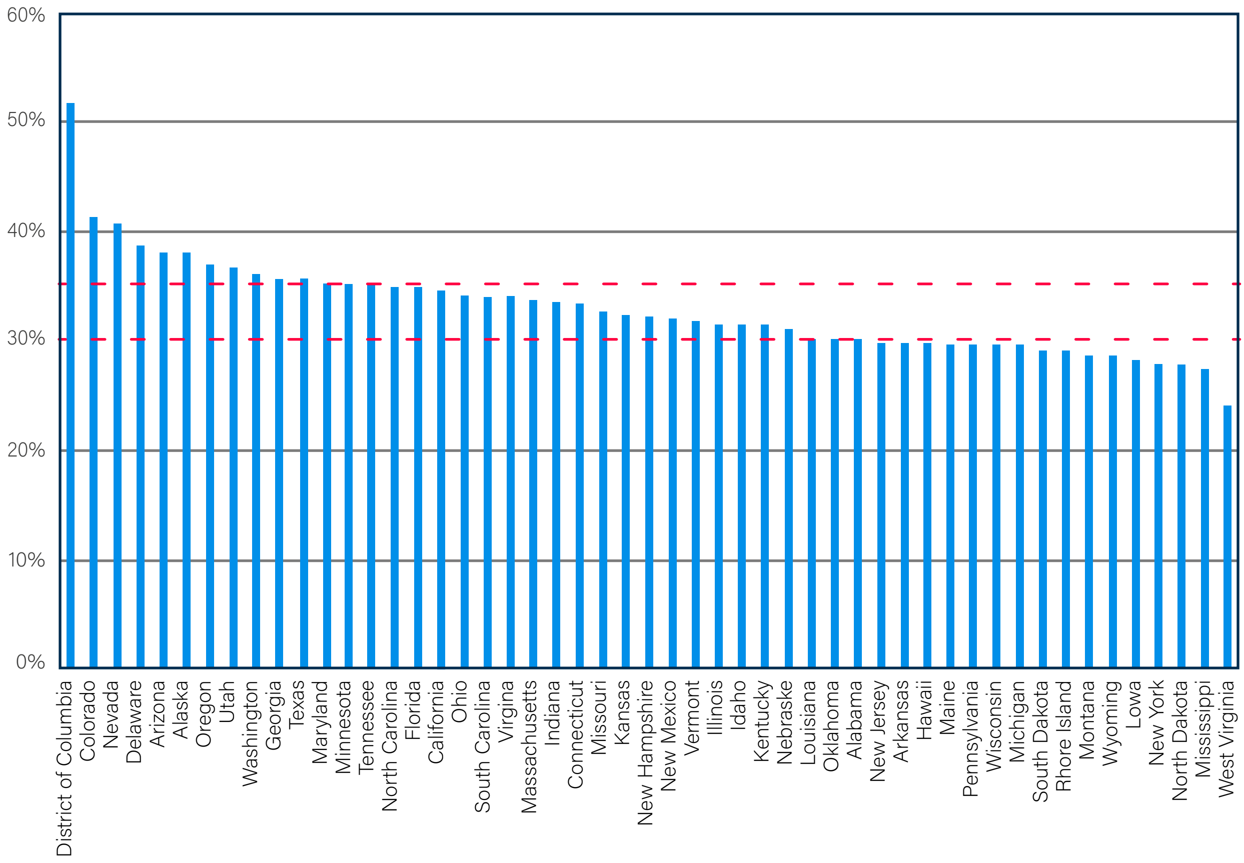
[8] *IDC Semiannual Public Cloud Services Tracker (2023H1 Release)*
[9] *The ABS covers all nonfarm businesses filing Internal Revenue Service tax forms as individual proprietorships, partnerships, or any type of corporation, and with receipts of $1,000 or more with paid employees. Converting to business with more than 10 employees for cross-country comparability purpose, the OECD adjusts cloud adoption to 44.29%.*

exceeding 35% (District of Columbia, Colorado, Nevada, Delaware, Arizona, Alaska, Oregon, Utah, Washington, Georgia, Texas, Maryland, Minnesota, Tennessee, and North Carolina) while sixteen states exhibited enterprise adoption below 30% (see Graphic 2-2).

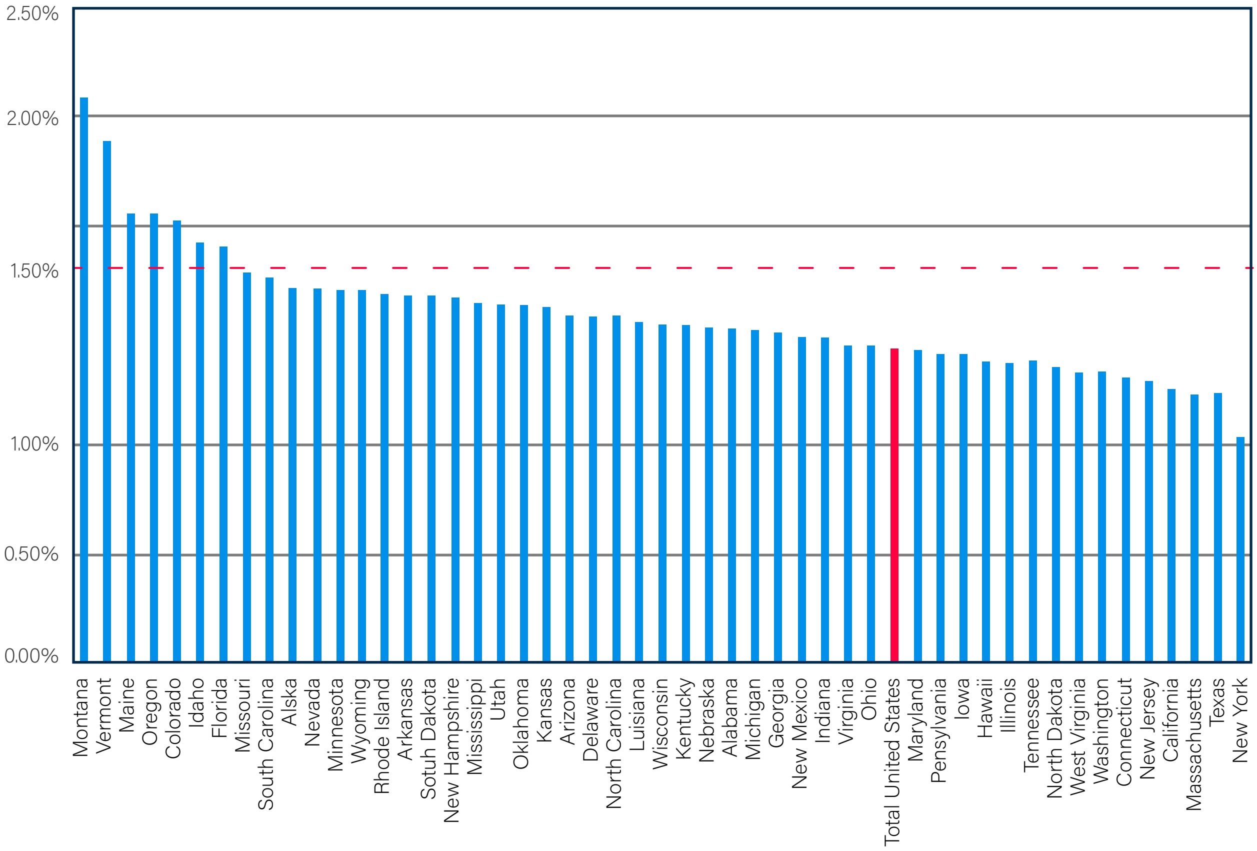
Graphic 2-2. United States: Cloud adoption (Percent of employer firms) (2018) (%)



Source: Census Bureau. Annual Business Survey (ABS)

Correlated with cloud adoption, cloud spending in 2022 by state indicates some clustering around a group of states exceeding 1.50% of GDP in the US: Montana, Vermont, Maine, Oregon, Colorado, Idaho, and Florida (see Graphic 2-3).

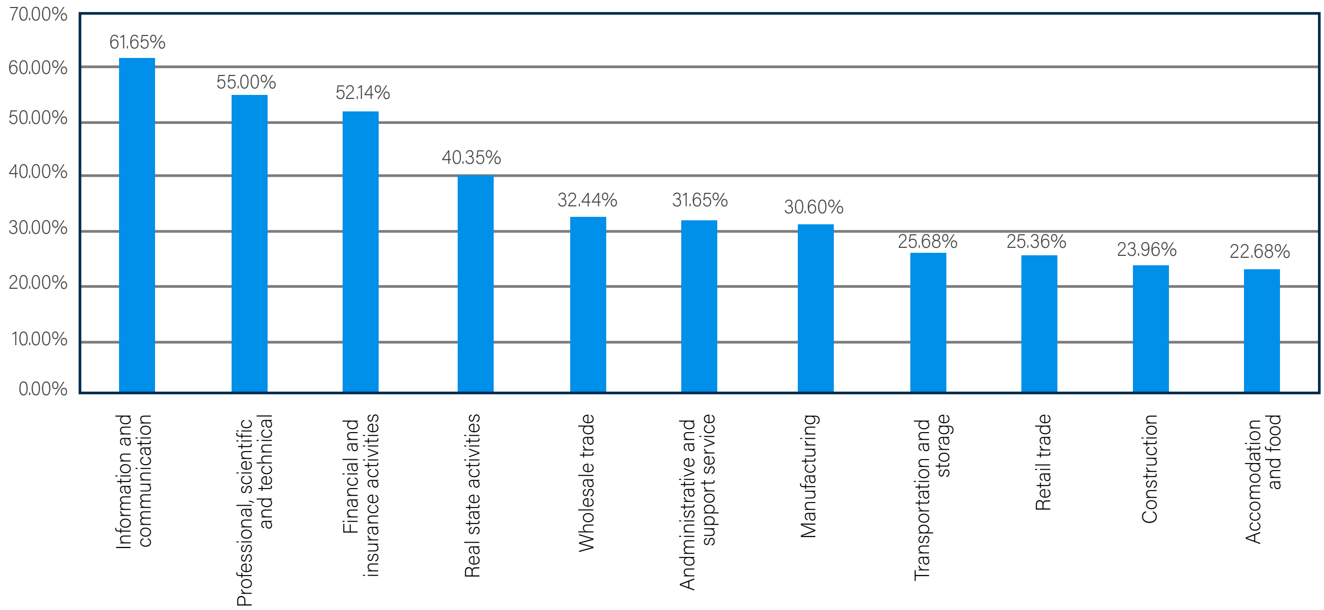
Graphic 2-3. United States: Cloud spending as percent of GDP (2022) (%)



Note: AI Platforms excluded from vendor revenues
Source: Census Bureau. Annual Business Survey (ABS); IDC; Telecom Advisory Services analysis

From an industrial sector perspective, cloud adoption is highest in: (i) Information and Communication, (ii) Professional, Scientific and Technical Services, and (iii) Financial and Insurance (see Graphic 2-4).

Graphic 2-4. United States: Cloud adoption (2018) (by sector) (%)



Source: Census Bureau. Annual Business Survey (ABS)

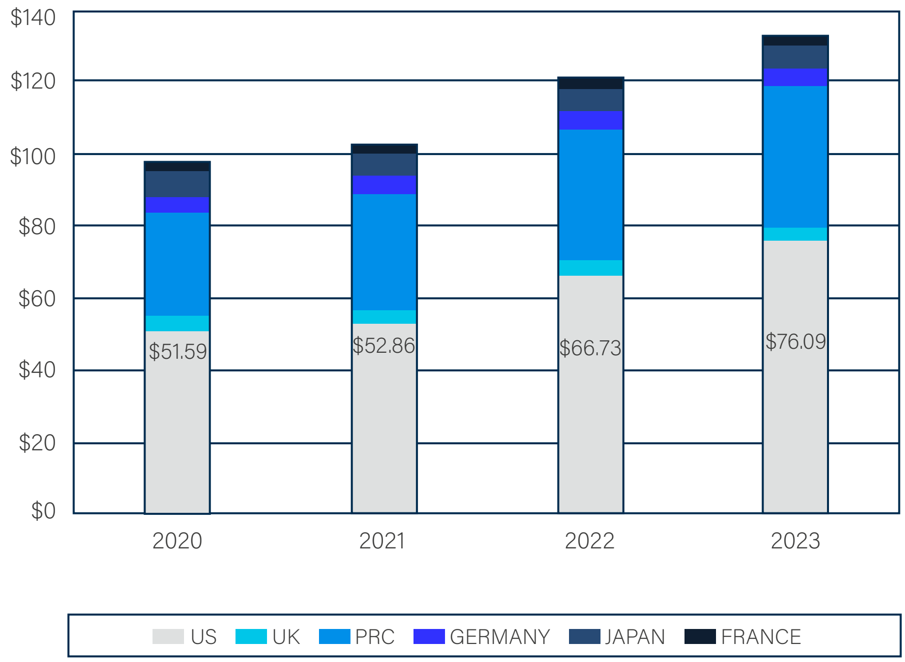
From a cloud supply standpoint, hyperscalers have a presence in California, Virginia, Ohio, Oregon, South Carolina, Iowa, Texas, Nevada, Utah, Georgia, Wyoming, Illinois, Washington, Arizona, and the District of Columbia. As of 2023, 49 cloud regions were deployed in the US with a total of 116 availability zones[10].

2.2. ARTIFICIAL INTELLIGENCE

As in the case of cloud computing, AI spending in the US is the largest in the world, amounting to US$ 76.1 billion[11] (or 45.5% of the global market) in 2023 (see Graphic 2-5).

[10] *Source: Telegeography.*
[11] *Source: IDC Semiannual Artificial Intelligence Infrastructure Tracker 2023H2.*

Graphic 2-5. Selected Advanced Economies: Cloud computing constant vendor revenues (in billions) (2018-2023)

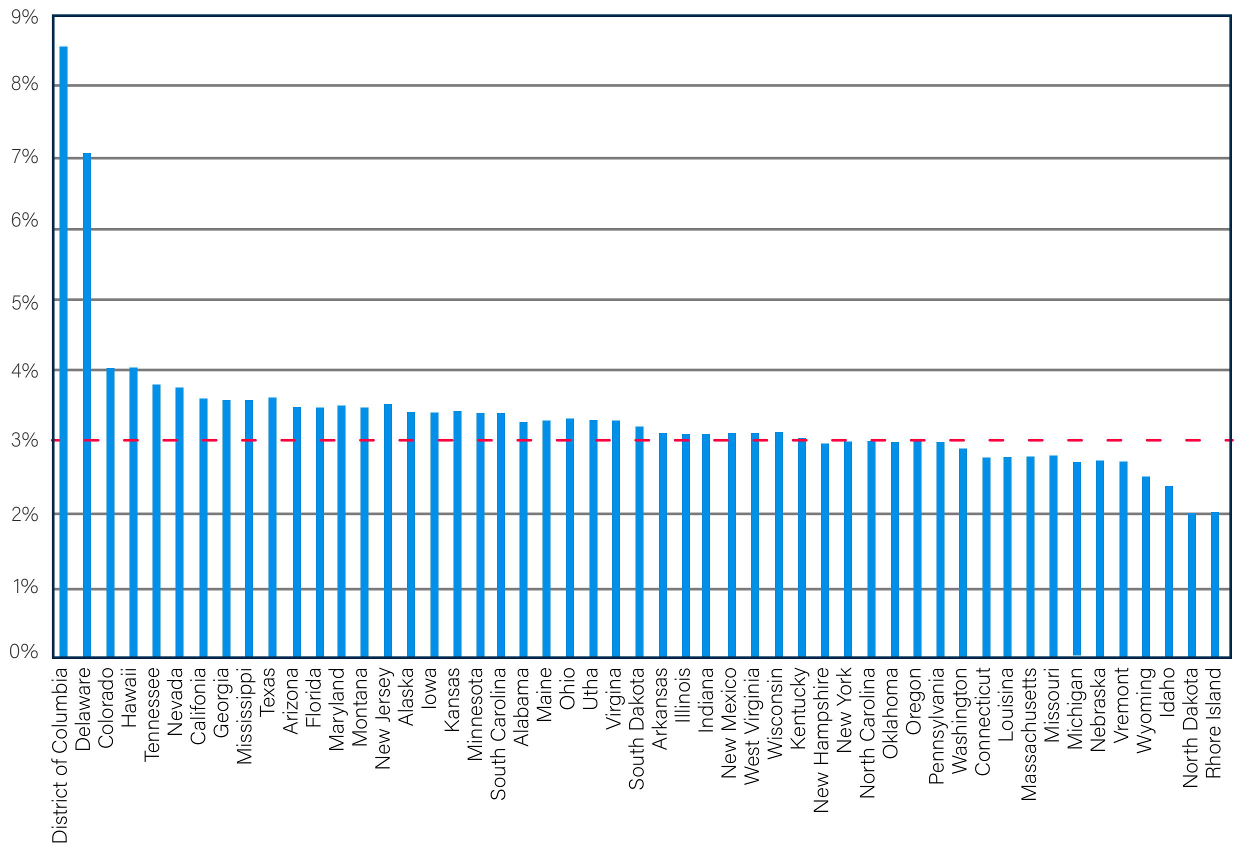


Source: IDC Semiannual Artificial Intelligence Infrastructure Tracker 2023H2.

In 2018, AI adoption in US enterprises had reached 3.46%.[12] Twenty-five states exhibited an AI enterprise adoption in excess of 3% (see Graphic 2-6).

[12] *The OECD adjusts AI adoption to 3.68% of business with more than 10 employees.*

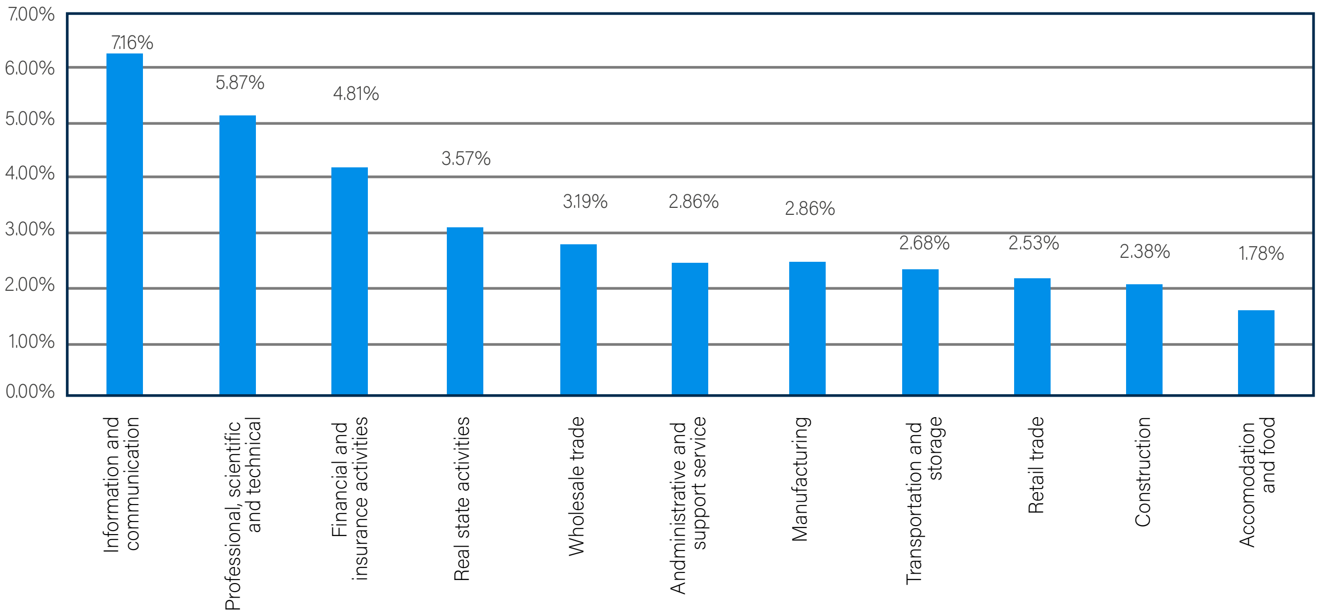
Graphic 2-6. United States: AI enterprise adoption (Percent of employer firms) (2018) (%)



Source: Census Bureau. Annual Business Survey (ABS), 2019

From a sector standpoint, AI adoption is highest in the same sectors as in the case of cloud (see Graphic 2-7).

Graphic 2-7. United States: AI enterprise adoption (2018) (by sector) (%)



Source: Census Bureau. Annual Business Survey (ABS), 2019

Extrapolating adoption based on the growth in spending, adoption is estimated to have reached 5.6% by 2022.

2.3. CLOUD COMPUTING AND CLOUD-ENABLED AI

Firms active in the AI supply chain comprise a whole range of hardware (chipsets, servers, and storage), software (general purpose, analytic toolkits, and industry specific platforms), and services (cloud provision, simulation, installation solutions, and advisory). The complementarity of cloud computing and AI addresses the specific provision of AI platforms by cloud computing service providers (CSPs) (see table 2-2).

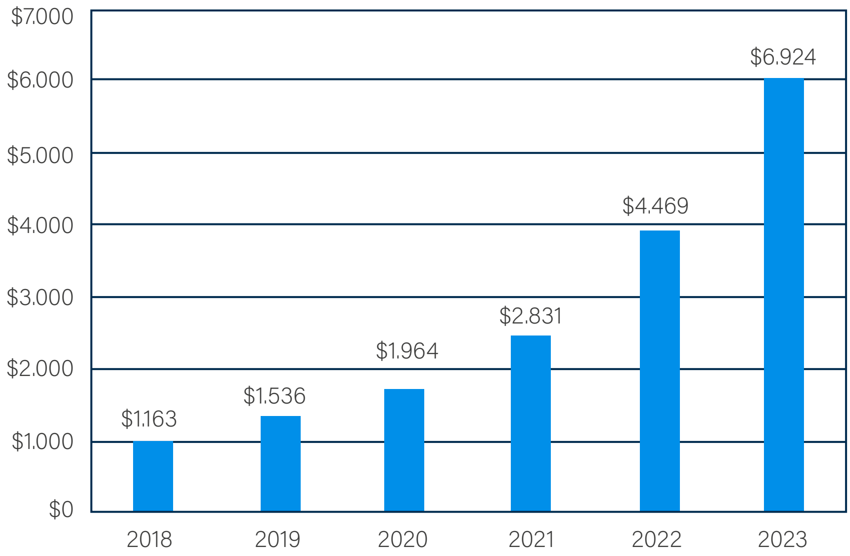
Table 2-2. AI platforms delivered by cloud service providers (CSPs)

Cloud Service Provider	AI Platforms
Alibaba Group	Alright
AWS	Bedrock, Sqrrl, Veeqo, Wickr
Cisco	BroadSoft, CloudCherry, Duo Security, Epsagon, Kenna Security, Opsani, Portshift
Google	Actifio, AppSheet, Cask Data, Intrigue, Looker, Mandiant, Playspace
Microsoft	AppNexus, Github, Nuance, RiskIQ

Source: Compiled by Telecom Advisory Services

Spending by enterprises in purchasing AI from CSPs in the US for 2023 amounts to US$ 6.92 billion (or 9.09% of the total AI market) and has been growing at 42.87% per year (see Graphic 2-8).

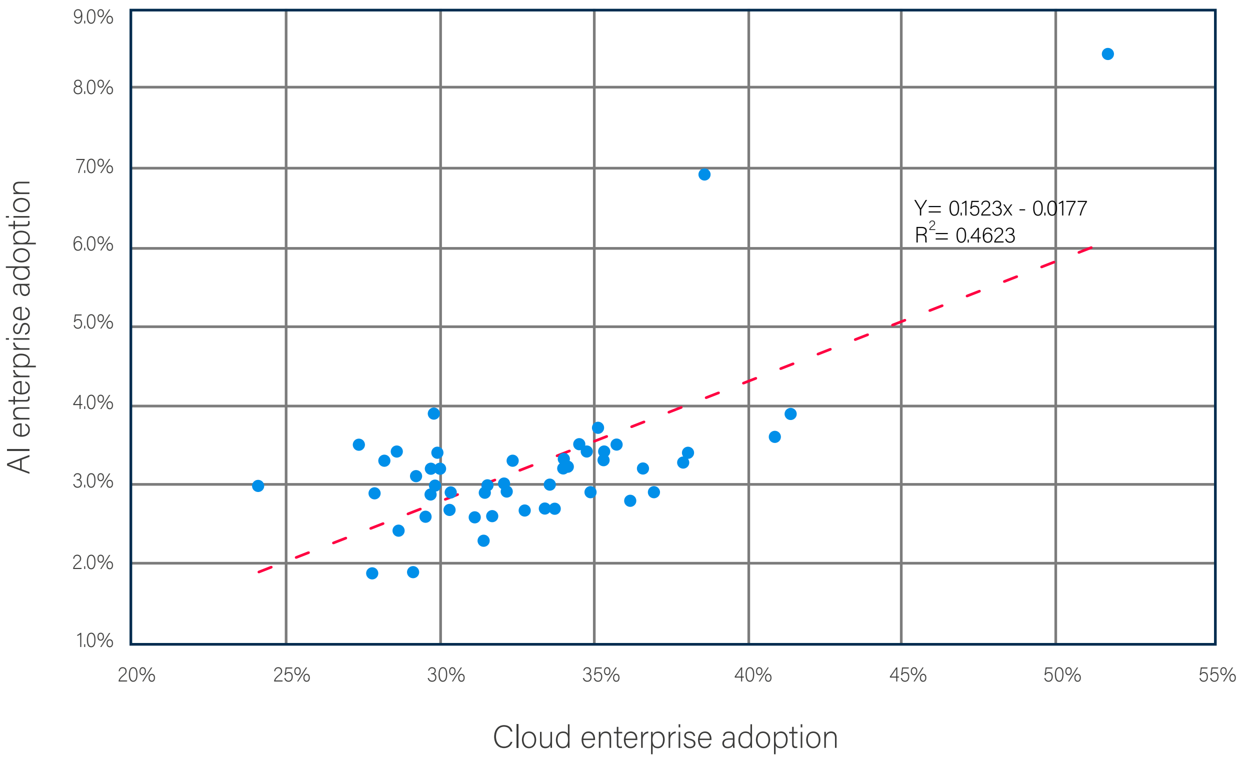
Graphic 2-8. United States: AI spending when delivered by CSPs (2018-2023) (in US$ billion)



Source: IDC Semiannual Public Cloud Services Tracker- 2023H1 Forecast

A very preliminary indication of the complementarity between cloud computing and AI is the correlation in adoption of both technologies when measured by state (see graphic 2-8).

Graphic 2-8. United States: Correlation of state adoption of cloud computing and AI (2018)



Source: Census Bureau. Annual Business Survey (ABS); Telecom Advisory Services analysis

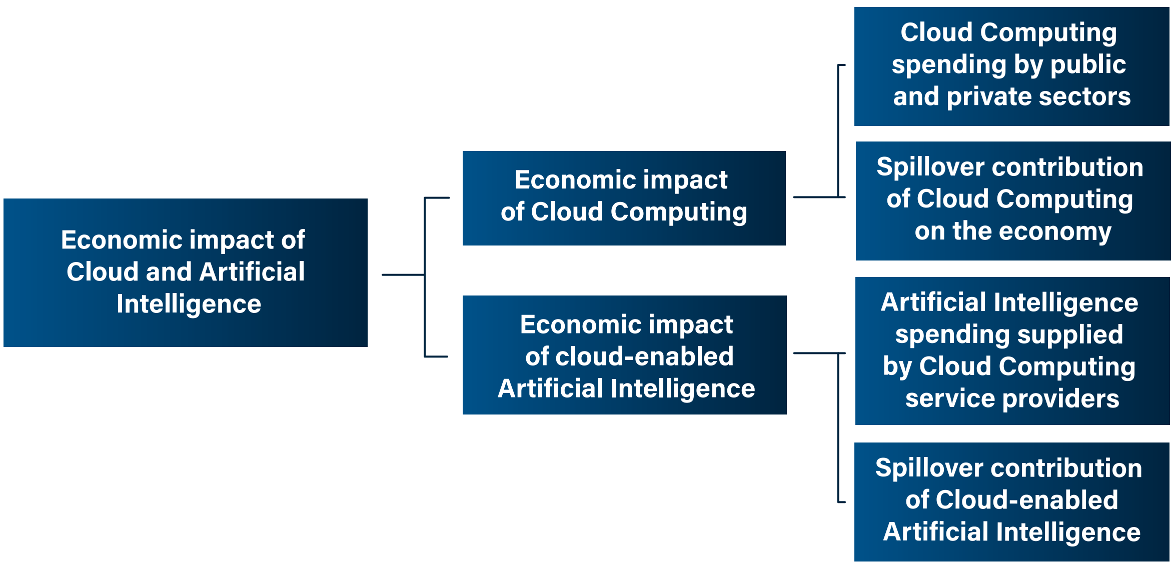
The correlation between cloud and AI enterprise adoption simply indicates the close association that exists between both technologies as driven by the average level of innovation in each state. It is critical to understand the causality existing between adoption of both technologies (in other words, determine whether the adoption of AI needs to rely on cloud computing) and their cumulative economic contribution. This will be addressed in the next section.

3. STUDY THEORETICAL MODEL

The focus of the study is to assess (i) the economic contribution of cloud computing as a technology and (ii) the complementary economic impact of cloud computing and AI in the US, differentiating by State and industrial sector.

The empirical strategy selected for this research is supported by a theoretical model that estimates spillover effects in economic output derived from cloud adoption and its potential complementarities with AI (see figure 3-1).

Figure 3-1. Study framework



The econometric analysis is based on a derivation of a Cobb–Douglas production function, where we expect that Total Factor Productivity (TFP), reflecting differences in productive efficiency across industries and countries, depends on cloud adoption by firms and AI use. This is reasonable since, as demonstrated in the review of the literature in Appendix A, both technologies are complementary.

These models, presented in detail in Appendix B, would allow us to estimate the contribution to GDP and productivity of: (i) cloud as an autonomous technology, (ii) cloud as an enabler to AI in the aggregate and for specific states in the US.

4. ECONOMETRIC MODELS AND RESULTS

To disentangle the effect of ICT-related variables on output, and its inverse, the following micromodel is formalized beyond the aggregated production equation (Table 4-1).

Table 4-1. System of simultaneous equations

Aggregate production equation		Y_{is}= f(K_{is}, L_{is}, $CLOUD_{is}$, AI_{is})
Cloud equations	Demand equation Supply equation Cloud infrastructure production	$CLOUD_{is}$=g($(Y/L)_{is}$,CLOUD $PRICE_{is}$, $STEM_{is}$, $SOFTWARE_{is}$,$URBAN_{is}$) CLOUD $REVENUE_{is}$=h(CLOUD $PRICE_{is}$, Y_{is}, CLOUD $PRODUCERS_{is}$) $\Delta CLOUD_{is}$=j(CLOUD $REVENUE_{is}$)
AI equations	Demand equation Supply equation AI infrastructure production	AI_{is}=k(Y/L_{is},AI $PRICE_{is}$, $STEM_{is}$, $SOFTWARE_{is}$,$URBAN_{is}$) AI $REVENUE_{is}$=v(AI $PRICE_{is}$, Y_{is},AI $PRODUCERS_{is}$) ΔAI_{is}=z(AI $REVENUE_{is}$)

Note: i and s denote respectively country and sector.
Source: Telecom Advisory Services

According to the econometric estimations (detailed in Appendix B), the main results can be summarized as follows:

- A 1% increase in cloud adoption will yield an increase of **0.079%** of the GDP in case of firms exhibiting **low AI use.**
- A 1% increase in cloud adoption will yield an increase of **0.114%** of the GDP in case of firms with **moderate AI use.**
- A 1% increase in cloud adoption will yield an increase of **0.147%** of the GDP in case of firms with **intensive AI use.**

5. ESTIMATING THE ECONOMIC IMPACT OF CLOUD COMPUTING AND CLOUD-ENABLED AI IN THE UNITED STATES

5.1. CLOUD ECONOMIC CONTRIBUTION

The aggregate economic contribution of cloud to GDP is composed of: (i) the domestic revenues generated by cloud service providers and (ii) the spillover effects of cloud services on the total economy. The revenues represent the spending of public and private organizations purchasing cloud services[13] , while the spillover effects are the benefits generated by cloud computing in terms of IT cost efficiencies, new product development, support for incubation of startups and the like[14]. By adding the economic benefits generated from the use of cloud services (the spillover effect) to the spending in cloud services (the direct effect) we obtain a measure of the total economic contribution (see table 5-1).

Table 5-1. Revenue and spillover contribution of cloud services to GDP

ITEM	Indicator	Source
(1)	Cloud spending by public and private sector	From Chapter 3
(2)	Spillover effect: Spill-over effect of cloud services	Calculated from elasticities in chapter 5
(3)	Total impact of cloud services to the GDP	(1) + (2)

Source: Telecom Advisory Services

Direct spending includes all revenues of cloud companies when they offer their services in the US.[15] To calculate direct spending, total cloud spending for the US (see section 3-1) is prorated by each combination of industry and state depending on the number of firms within each observation that purchase cloud services (and also assuming constant cloud spending across firms).

To estimate the spillovers from cloud adoption growth in 2022 we developed a simple regression linking cloud adoption with cloud expenditure, with state and industry fixed effects. The results would suggest that a 1% increase in cloud spending is linked to an increase in cloud adoption of 0.206%.

By applying this elasticity to the spending growth rates estimated for direct effects, it is possible to infer specific growth rates for cloud adoption in 2022, and therefore, to estimate the spillovers associated with it according to the elasticities derived in Table 4-4. Once estimations were done for all combinations of states and industries, total economic contribution of cloud computing for the US is calculated (see Table 5-2).

[13] The revenues are a measure of market demand that can be met through cloud providers based within the country or beyond the country's borders.
[14] For example, when cloud services enable the adoption of IT services in the SME sector, which benefits from the scalability of IT state-of-the-art, that is considered to be a spillover effect.
[15] The revenues derived from offering AI platforms are excluded since they will be added in the estimation of complementarity between AI and cloud in section 6.2.

Table 5-2. United States: Total economic contribution of cloud computing (2022) (in US$ billions)

ITEM	Indicator	Source
(1)	Cloud spending by public and private sector	$ 303.53
(2)	Spillover effect: Spill-over effect of cloud services	$ 101.06
(3)	Total impact of cloud services to the GDP	$ 404.59

Source: Telecom Advisory Services

In conclusion, the total economic impact of cloud in the US in 2022, comprising cloud spending and its spillovers on the economy, is sizable: US$ 404.59 billion. Our projections for 2023 and 2024 allow us to estimate a total GDP contribution of cloud computing increasing to US$ 434 and US$ 502 billion, respectively.

5.2. ECONOMIC CONTRIBUTION OF CLOUD-ENABLED AI

The quantification of the economic contribution of AI economic value delivered as a complementary technology requires, as in the prior case, to estimate spending and spillovers.

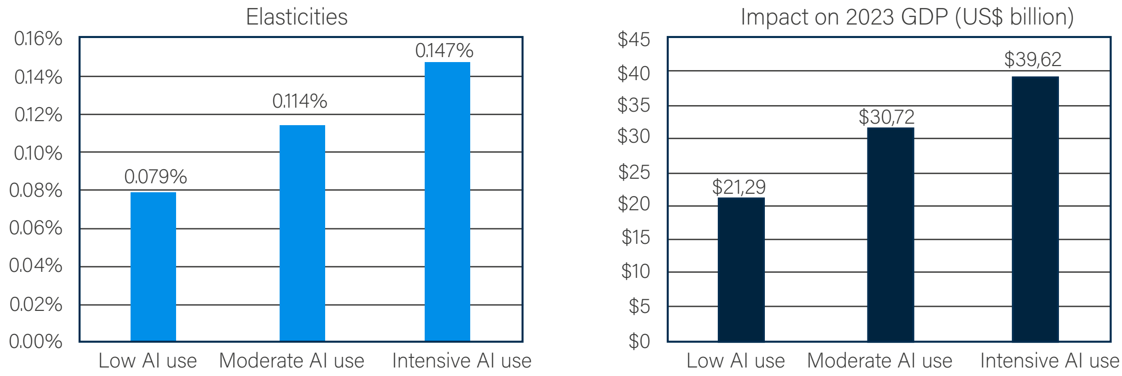
IDC provides an estimate of the revenues generated by cloud service providers in delivering artificial intelligence platforms. Spending in this category in the US for 2022 amounts to US$ 4.46 billion.

To calculate spillovers derived from complementarity between AI and cloud computing in 2022, we use the coefficients resulting from the most conservative estimations of the output equation (see Appendix B). To reiterate, the elasticities resulting from this model are the following:

- A 1% increase in cloud adoption will yield an increase of **0.079%** of the GDP in case of firms exhibiting **low AI use.**
- A 1% increase in cloud adoption will yield an increase of **0.114%** of the GDP in case of firms with **moderate AI use.**
- A 1% increase in cloud adoption will yield an increase of **0.147%** of the GDP in case of firms with **intensive AI use.**

These elasticities allow estimating GDP contribution by level of AI use (see graphic 5-1).

Graphic 5-1. United States: Spillover impact of AI as complimentary to cloud



Source: Bureau of Economic Analysis; Telecom Advisory Services analysis

These coefficients were applied to all combinations of industry and state, according to their respective intensity of AI use (see table in appendix A-2), with the resulting estimates (see table 5-3).

Table 5-3. United States: Total economic contribution of AI as complementary to cloud computing (2022) (in US$ billions)

ITEM	Indicator	Source
(1)	Expenditure on AI supplied by Cloud Service Providers	US$ 4.469
(2)	Spillover from Cloud enabled AI	US$ 65.389
(3)	Total impact of Cloud-enabled AI to GDP	US$ 69.859

Source: Telecom Advisory Services

In conclusion, the economic contribution to GDP derived from AI as a complementary to cloud amounted to US$ 69.86 billion (estimated to account for US$ 57 billion in 2023 and US$ 64 billion in 2024).

In addition to estimating the impact for 2022 for cloud and the complementarity between cloud and AI, we forecast economic contribution for the ten-year interval (see table 5-3).

Table 5-3. United States: Economic contribution of cloud computing and AI (in US$ billions) (2022-2031)

Year	Cloud computing			Cloud-enabled AI		
	Spending	Spillover	Total	Spending	Spillover	Total
2022	$ 303.53	$ 101.06	$ 404.59	$ 4.47	$ 65.39	$ 69.86
2023	$ 356.98	$ 77.10	$ 434.08	$ 6.92	$ 49.89	$ 56.81
2024	$ 420.77	$ 81.19	$ 501.96	$ 11.01	$ 52.54	$ 63.55
2025	$ 493.88	$ 82.00	$ 575.88	$ 17.70	$ 53.06	$ 70.76
2026	$ 576.94	$ 82.58	$ 659.52	$ 28.71	$ 53.44	$ 82.15
2027	$ 670.34	$ 82.66	$ 753.00	$ 43.75	$ 53.49	$ 97.24
2028	$ 804.07	$ 105.95	$ 910.02	$ 90.07	$ 68.56	$ 158.63
2029	$ 942.54	$ 94.58	$ 1,037.12	$ 110.72	$ 61.20	$ 171.92
2030	$ 1,104.87	$ 97.87	$ 1,202.73	$ 134.60	$ 63.32	$ 197.93
2031	$ 1,295.15	$ 101.15	$ 1,396.30	$ 161.72	$ 65.45	$ 227.17

Source: IDC Semiannual Public Cloud Services Tracker- 2023H1 Forecast; Telecom Advisory Services analysis

Over a ten-year timeframe (2022-2031), the economic impact of cloud in the US is significant, reaching US$ 7.87 trillion (or 2.55% of the forecasted cumulative GDP), while **the impact of AI** as a technology complementary to cloud will reach **US$ 1.19 trillion** (or 0.39% of the forecasted cumulative GDP).

5.3. ESTIMATING ECONOMIC IMPACT BY STATE

On the basis of the estimates presented above, we estimated the differential economic impact across states and industries in the country. Strictly speaking, differences in economic impact could be traced back to the variance in cloud and AI adoption, on the number of firms adopting cloud by sector, and on the sectoral growth rates of cloud spending.

Cloud spillovers depend on AI intensity. More precisely, for the average State, an increase of 1% in cloud adoption yields a GDP increase of 0.115%. This is equivalent to $807 million in Virginia, $1 billion in Ohio, and $4.6 billion in California.

The estimates were calculated for a selected list of States for 2023 (see table 5-4).

Table 5-4: United States: Economic contribution of cloud computing and AI (in US$ millions) (2023)

Year	Cloud computing			Cloud-enabled AI			Total economic impact	
	Spending	Spillover	Total	Spending	Spillover	Total	Value (B$)	% of GDP
Arizona	$7,342.42	$1,674.01	$9,016.42	$138.65	$1,088.18	$1,226.83	$10,243.25	1.96%
California	$44,407.60	$12,423.51	$56,831.12	$877.86	$8,724.14	$9,602.00	$66,433.12	1.72%
Georgia	$11,246.45	$2,624.67	$13,871.12	$224.71	$1,927.82	$2,152.53	$16,023.65	1.93%
Illinois	$13,703.74	$3,517.04	$17,220.78	$278.13	$2,053.87	$2,332.00	$19,552.78	1.78%
Maryland	$6,660.40	$1,512.57	$8,172.97	$128.62	$1,010.72	$1,139.33	$9,312.31	1.81%
Mississippi	$2,235.61	$439.40	$2,675.01	$55.51	$267.14	$322.65	$2,997.66	1.98%
Nevada	$3,704.38	$838.68	$4,543.06	$65.86	$510.73	$576.59	$5,119.65	2.08%
Ohio	$11,618.43	$2,778.47	$14,396.90	$213.24	$1,897.24	$2,110.47	$16,507.37	1.87%
Oregon	$5,913.47	$1,015.32	$6,928.80	$106.12	$627.08	$733.20	$7,662.00	2.40%
Pennsylvania	$12,542.24	$3,116.78	$15,659.02	$266.30	$1,766.25	$2,032.55	$17,691.57	1.81%
Virginia	$9,363.24	$2,179.98	$11,543.22	$170.55	$1,243.99	$1,414.55	$12,957.77	1.80%

Source: Telecom Advisory Services analysis

In order to provide more detail on the state contributions, we present here some selected cases of industries within each state. In Table 5-5 we present the specific cases of the Financial Services & Insurance, Information Industry, Manufacturing, as well as Transportation and Storage sectors across the following states: Arizona, California, Georgia, Illinois, Maryland, Mississippi, Nevada, Ohio, Oregon, Pennsylvania, and Virginia.

Table 5-5. Total economic impact of Cloud computing in selected sectors and states (2022) – including AI complementarity

State	Sector	Cloud spending growth rate	Cloud spending 2022 ($ M)	Cloud adoption growth (%)	Elasticity cloud adoption – GDP (%)	Cloud spillovers (% GDP)	Cloud spillovers ($ M)	Total impact ($ M)
Arizona	Finance Services & insurance	25.81%	$ 560.29	5.31%	0.15%	0.78%	$ 871.52	$ 1,431.81
	Information Industry	24.94%	$ 192.86	5.13%	0.15%	0.75%	$ 121.51	$ 314.38
	Manufacturing	24.56%	$ 175.46	5.05%	0.11%	0.58%	$ 226.93	$ 402.39
	Transportation and Storage	19.58%	$ 111.53	4.03%	0.15%	0.59%	$ 108.53	$ 220.06
California	Finance Services & insurance	25.81%	$ 3,082.31	5.31%	0.15%	0.78%	$ 5,266.57	$ 8,348.88
	Information Industry	24.94%	$ 1,865.52	5.13%	0.15%	0.75%	$ 2,904.83	$ 4,770.35
	Manufacturing	24.56%	$ 1,357.32	5.05%	0.15%	0.74%	$ 2,947.60	$ 4,304.92
	Transportation and Storage	19.58%	$ 692.26	4.03%	0.11%	0.46%	$ 561.23	$ 1,253.49

State	Sector	Cloud spending growth rate	Cloud spending 2022 ($ M)	Cloud adoption growth (%)	Elasticity cloud adoption – GDP (%)	Cloud spillovers (% GDP)	Cloud spillovers ($ M)	Total impact ($ M)
Georgia	Finance Services & insurance	25.81%	$ 729.37	5.31%	0.15%	0.78%	$ 1,258.91	$ 1,988.29
	Information Industry	24.94%	$ 340.78	5.13%	0.15%	0.75%	$ 387.49	$ 728.27
	Manufacturing	24.56%	$ 292.70	5.05%	0.15%	0.74%	$ 542.26	$ 834.97
	Transportation and Storage	19.58%	$ 195.31	4.03%	0.11%	0.46%	$ 157.91	$ 353.21
Illinois	Finance Services & insurance	25.81%	$ 1,029.36	5.31%	0.15%	0.78%	$ 1,670.20	$ 2,699.56
	Information Industry	24.94%	$ 421.17	5.13%	0.15%	0.75%	$ 281.69	$ 702.86
	Manufacturing	24.56%	$ 473.83	5.05%	0.11%	0.58%	$ 726.83	$ 1,200.66
	Transportation and Storage	19.58%	$ 406.85	4.03%	0.15%	0.59%	$ 268.61	$ 675.46
Maryland	Finance Services & insurance	25.81%	$ 456.93	5.31%	0.15%	0.78%	$ 747.56	$ 1,204.49
	Information Industry	24.94%	$ 185.36	5.13%	0.15%	0.75%	$ 159.91	$ 345.27
	Manufacturing	24.56%	$ 124.71	5.05%	0.11%	0.58%	$ 147.18	$ 271.89
	Transportation and Storage	19.58%	$ 67.85	4.03%	0.11%	0.46%	$ 55.05	$ 122.90
Mississippi	Finance Services & insurance	25.81%	$ 245.72	5.31%	0.15%	0.78%	$ 172.84	$ 418.56
	Information Industry	24.94%	$ 55.77	5.13%	0.15%	0.75%	$ 22.01	$ 77.78
	Manufacturing	24.56%	$ 49.08	5.05%	0.15%	0.74%	$ 156.25	$ 205.32
	Transportation and Storage	19.58%	$ 43.22	4.03%	0.11%	0.46%	$ 28.99	$ 72.20
Nevada	Finance Services & insurance	25.81%	$ 230.30	5.31%	0.15%	0.78%	$ 353.31	$ 583.61
	Information Industry	24.94%	$ 121.25	5.13%	0.15%	0.75%	$ 46.31	$ 167.55
	Manufacturing	24.56%	$ 73.03	5.05%	0.15%	0.74%	$ 74.13	$ 147.16
	Transportation and Storage	19.58%	$ 71.89	4.03%	0.15%	0.59%	$ 64.61	$ 136.49
Ohio	Finance Services & insurance	25.81%	$ 1,133.05	5.31%	0.15%	0.78%	$ 1,443.83	$ 2,576.88
	Information Industry	24.94%	$ 305.91	5.13%	0.15%	0.75%	$ 147.69	$ 453.59
	Manufacturing	24.56%	$ 524.84	5.05%	0.15%	0.74%	$ 932.52	$ 1,457.36
	Transportation and Storage	19.58%	$ 238.55	4.03%	0.08%	0.32%	$ 94.92	$ 333.46
Oregon	Finance Services & insurance	25.81%	$ 369.18	5.31%	0.15%	0.78%	$ 426.85	$ 796.03
	Information Industry	24.94%	$ 193.13	5.13%	0.15%	0.75%	$ 94.45	$ 287.58
	Manufacturing	24.56%	$ 199.44	5.05%	0.11%	0.58%	$ 211.62	$ 411.06
	Transportation and Storage	19.58%	$ 92.43	4.03%	0.15%	0.59%	$ 57.89	$ 150.32

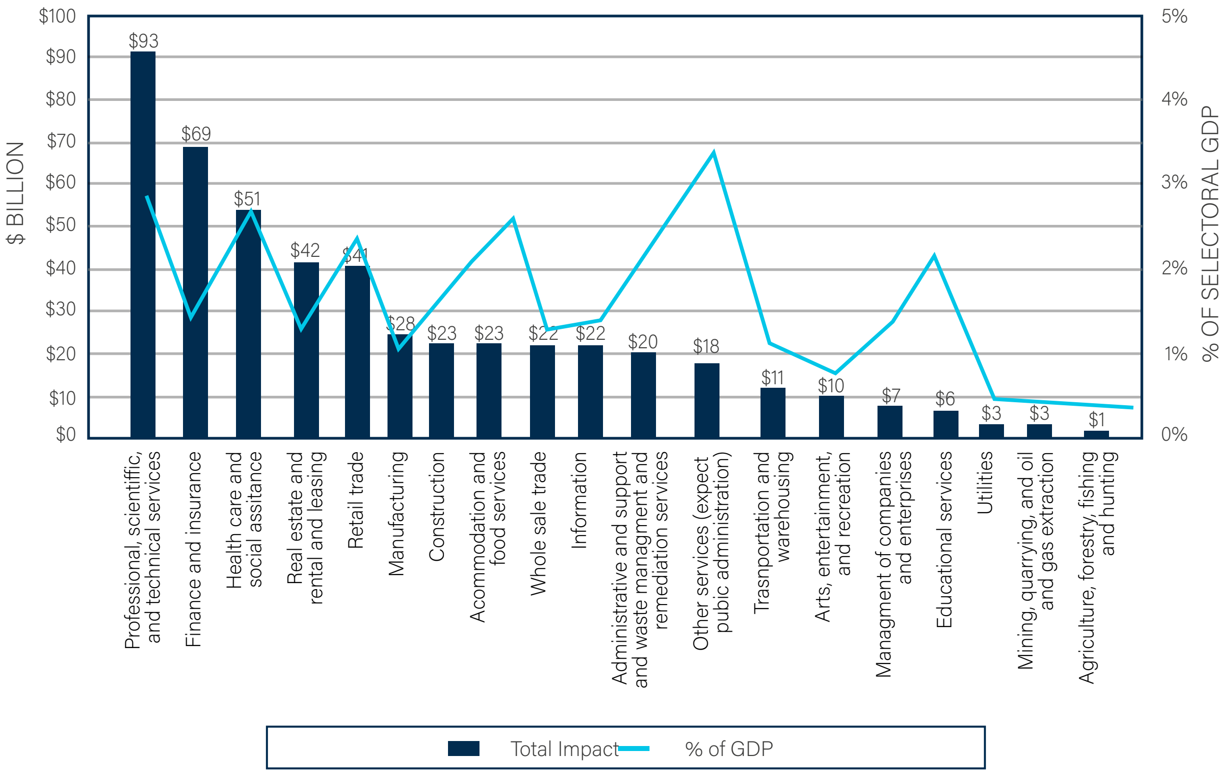
State	Sector	Cloud spending growth rate	Cloud spending 2022 ($ M)	Cloud adoption growth (%)	Elasticity cloud adoption – GDP (%)	Cloud spillovers (% GDP)	Cloud spillovers ($ M)	Total impact ($ M)
Pennsylvania	Finance Services & insurance	25.81%	$ 1,160.42	5.31%	0.15%	0.78%	$ 1,349.85	$ 2,510.27
	Information Industry	24.94%	$ 419.12	5.13%	0.15%	0.75%	$ 337.56	$ 756.68
	Manufacturing	24.56%	$ 421.95	5.05%	0.15%	0.74%	$ 770.73	$ 1,192.68
	Transportation and Storage	19.58%	$ 201.52	4.03%	0.15%	0.59%	$ 228.35	$ 429.88
Virginia	Finance Services & insurance	25.81%	$ 664.69	5.31%	0.11%	0.61%	$ 763.90	$ 1,428.59
	Information Industry	24.94%	$ 297.42	5.13%	0.15%	0.75%	$ 207.46	$ 504.88
	Manufacturing	24.56%	$ 216.49	5.05%	0.15%	0.74%	$ 369.20	$ 585.69
	Transportation and Storage	19.58%	$ 130.49	4.03%	0.08%	0.32%	$ 61.57	$ 192.05

Source: Telecom Advisory Services analysis

The results presented in Table 5-5 are naturally affected by scale differentials: it is not a surprise to appreciate the largest economic impact in California, as this is the biggest state across the selected sample. If we weight the economic impact by their respective GDP, it is in the Information sector across the selected states and sectors where the largest economic impact is found: Nevada (2.73%), Ohio (1.96%), Oregon (2.32%), Arizona (1.95%), Illinois (1.88%), Virginia (1.83%), Pennsylvania (1.69%) and Maryland (1.63%). The lowest levels are in the transportation and storage sector in Virginia (0.99%), Maryland (1.02%) and California (1.03%), and in the manufacturing sector in Illinois (0.95%).

If we expand the analysis to the national level for a larger group of industrial sectors as represented in Graphic 6-1, results suggest the largest economic impact in the Professional, scientific, and technical service sector, followed by Finance, Health, Real Estate, Retail trade, manufacturing, and Information. As a share of GDP, it is in other services and in the Accommodation and Food industry where the largest effects are found (3.39% and 2.81% of their respective GDP). Lowest impact levels are identified for the agriculture, mining, and utilities industries

Graphic 6-1. United States: Economic impact of Cloud Computing in selected sectors (2022)

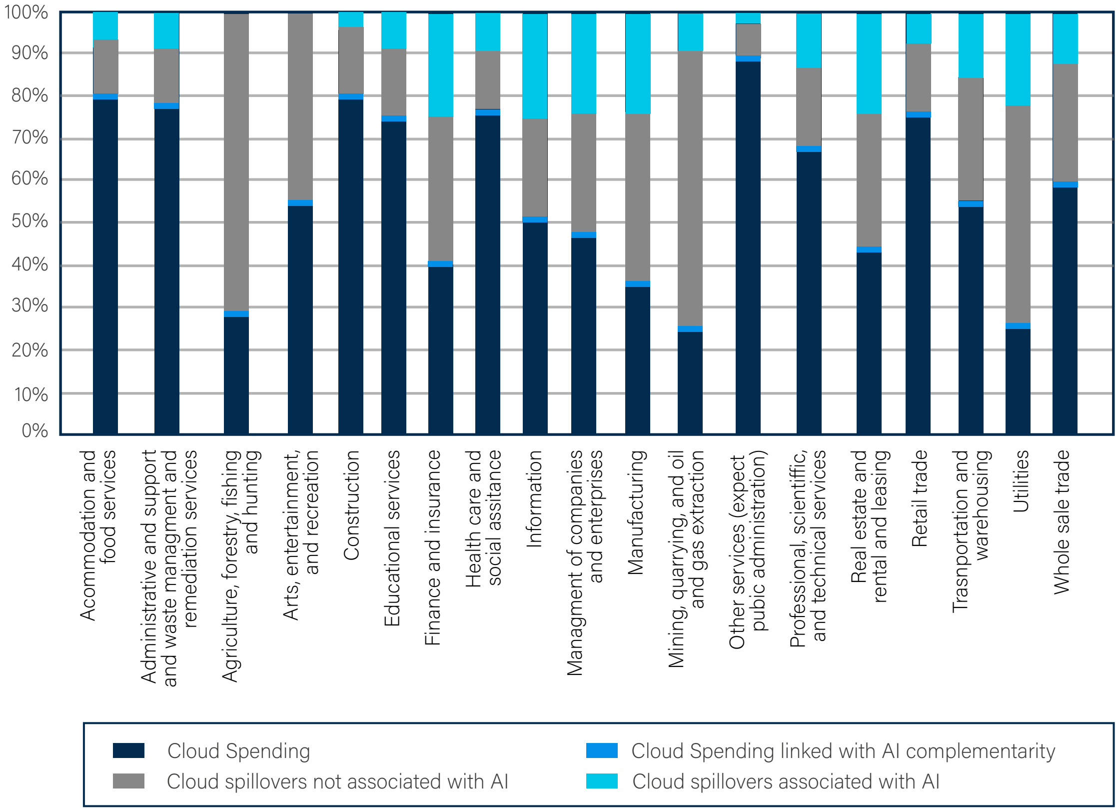


Source: Telecom Advisory Services analysis

There are some peculiarities in the two series presented in Graphic 6-1 that are worth observing. For instance, the other services sector presents a lower-than-average impact, while it represents an important share of the GDP. This is mainly explained due to the existence of several small establishments within this industry, which means that spending is high according to our calculations (as we are assuming a constant spending by firm). Something similar happens in the educational and accommodation and food services, although in these cases the high effect with respect to their GDP is also explained by important spillovers derived from the AI adoption in these industries.

The composition of the effect in each sector varies largely, depending on the intensiveness of each in using AI, the growth rate of adoption levels, and the number of firms adopting cloud (Graphic 6-2).

Graphic 6-2. United States: Economic impact of Cloud Computing in selected sectors by source of impact (2022)



Source: Telecom Advisory Services analysis

The models allow us to draw the following conclusions:

- The average elasticity in cloud-AI advanced states is 0.15% while the equivalent for the other states is 0.11% and 0.08% (moderately advanced and lagging, respectively).
- **While the average ten-year economic contribution of cloud for the US is 2.55% of the GDP, the impact when considering AI complementarity adds a further 0.39% of the GDP, yielding a total economic impact of 2.94% of the GDP.**
- **States that depict higher cloud adoption yield proportionally more economic gains from AI.** For example, a medium intensive AI sector with 30% cloud adoption will see their GDP increase in 0.52%, after increasing in 1% AI adoption.[16] The corresponding elasticity for a sector with 50% cloud adoption will be 0.58%.

[16] *Based on the average AI values of the sample*

- Accordingly, these results suggest that states which support a more pro-active approach to cloud development, are over performing in terms of AI economic impact.

- In some industrial sectors, the main effects are linked to direct spending (professional activities, health, retail and wholesale trade, accommodation and food). In the other industrial sectors, the spillovers are the main source of impact. In some industrial sectors, the spillovers from AI complementarity are significant (financial services and insurance, real estate, manufacturing, information industry, utilities), while in others these AI-enhancing effects are negligible due largely to low levels of AI adoption (agriculture, arts, other services).

6. ESTIMATION OF GENERATIVE AI ECONOMIC IMPACT

The econometric model developed to estimate the economic impact of cloud-enabled AI adoption presented in section 5 is mainly based on AI applications that precede generative AI since data on AI adoption in the ABS Survey as compiled in 2018. It is therefore safe to assume that companies responding in the affirmative at this point refer mostly to machine learning applications.[17]

Since their launch at the end of 2022, generative AI models have moved from being "modular specialists" (generating images from captions, transcribing text to speech) to getting integrated into applications such writing assistance, coding, translation in multiple industries. Most research conducted up to date on the economic impact of generative AI refers to its potential for enhancing productivity. Brynjolfsson, Li, and Raymond (2023) studied the impact of AI-based conversational assistant in customer care on agent productivity, and determined a productivity increase of 14%, as measured by issues resolved per hour. The effect results from disseminating behavior of most productive agents through the workforce, therefore benefitting less experienced workers. While the prior research was based on a real-world setting, Noy and Zhang (2023) analyzed the productivity effect of generative AI in an online experiment of mid-level college-level professionals (marketeers, grant writers, HR professionals) confronted with occupation-specific writing tasks. The productivity effect of the treatment group benefitting from the use of ChatGPT increased 37% of a task required 30 minutes to be completed. Eloundou et al. (2023) conducted an occupational analysis of the US workforce based on the O*NET database, an analysis similar to the one conducted by Frey and Osborne (2017) to assess the impact of machine learning. Each occupation is subjectively rated in terms of their potential to be impacted by Large Language Models by experts. The study estimates that with the basic capability of Large Language models, 15% of all worker tasks in the US could be completed "faster with the same level of quality. When incorporating software and tooling built on top of LLMs, this share increases to between 47 and 56% of all tasks." A similar analysis based on assessment of occupations in the O*NET database was conducted by Briggs and Kodnani (2023), concluding that 25% of US employment is at least partially exposed to generative AI. Based on this estimate, the authors estimate that widespread adoption of generative AI could raise overall labor productivity between 0.3 to 3.0 percentage points per year, although this is contingent upon, among other things the speed of adoption of the technology (see range of scenarios in table 6-1).

[17] *ChatGPT-3, developed by OpenAI was released on November 30, 2022. ChaptGPT-4, the paid version was introduced on March 14, 2023. Bard, developed by Google, was launched on March 21, 2023. Claude, developed by Anthropic, was originally released in March 2013, and a version 2 was introduced in July 2023. Companies gain access to these platforms and models to build and scale applications by accessing cloud services such as Microsoft Azure and Amazon Web services.*

Table 6-1. Generative AI impact on aggregate labor productivity

Scenario	Impact (in percentage points)
Much less powerful AI	0.3
Slower adoption (30 years)	0.5
Slower adoption (20 years)	0.7
Slightly less powerful AI	0.8
No labor displacement	1.3
Baseline	1.5
Slightly more powerful AI	2.4
More labor displacement	2.4
Much more powerful AI	2.9

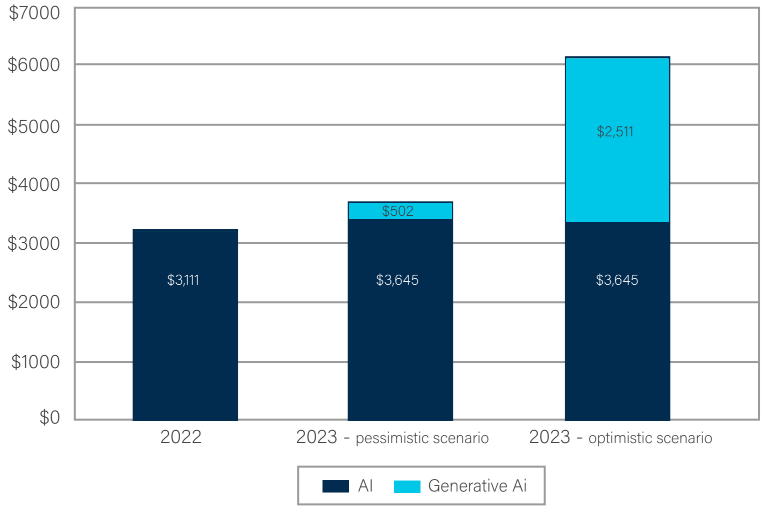
Source: Briggs and Kodnani (2023)

While generative AI is a subfield of machine learning, its demand for computing power is exponentially higher, which can be met by cloud service providers. Along these lines, a potential extrapolation of economic impact, when considering generative AI, could be based on an increase of AI adoption (by running sensitivity analysis on the demand equation of the AI set of equations in table 5-6). However, re-running the econometric model purely based on an increase in adoption would be underestimating its economic impact as a result of the implementation of new use cases (enhanced revenue), and an enhancement of labor productivity. Another way of approaching this extrapolation would be to rely on the range of productivity impact on the elasticity coefficients presented in table 6-1.

Labor productivity in the US was an average of $ 160,854 dollars per worker in 2022, according to the IMF. This productivity is expected to increase in 2023, in part because of AI developments, including generative AI. AI adoption in enterprises is expected to increase from 4.94% in 2021, to 5.57% in 2022 and 6.27% in 2023, according to estimations based on AI spending provided by Statista and the elasticity that links AI spending with adoption according to econometric models. These are annual increases of 12.6% in adoption levels, a considerable figure. According to the most conservative coefficient linking AI with productivity growth in table 5-5, the increase in AI adoption enhanced productivity levels, by adding $ 3,111 per worker in 2022 and $ 3,645 per worker in 2023. However, these estimates are not considering the accelerating factor that can be attributed to generative AI, as the regression coefficients come from a period of analysis before the wide diffusion of generative AI. By adding the impacts on labor productivity presented in Table 7-1 that can be attributed exclusively to generative AI, we can calculate an estimate of the enhancing effect generated by generative AI.

We take as a reference two elasticities presented in table 6-1. On the one hand, the most pessimistic scenario, 0.3% increase in labor productivity because of generative AI. On the other hand, we will also present an optimistic scenario, based on the 1.5% increase in labor productivity. The estimate of the AI effects on labor productivity, including both scenarios associated with generative AI, are presented in Graphic 6-1.

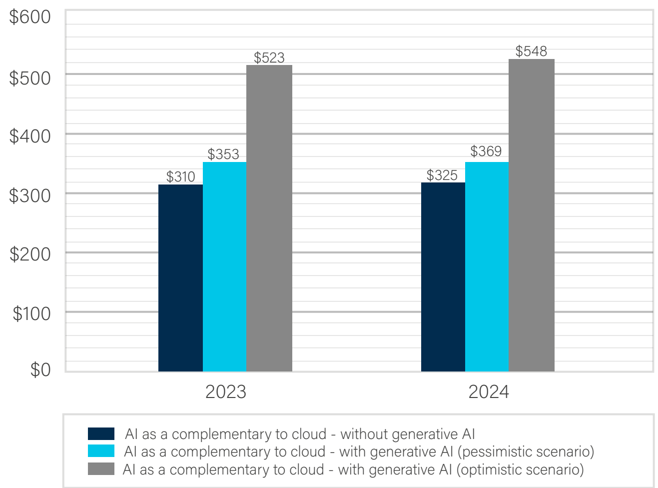
Graphic 6-1. United States: AI spillovers with the accelerating effect of Generative AI (dollars per worker)



Source: Telecom Advisory Services analysis

This means that the accelerated effect of generative AI would account for 13.78% of the original $3,645 effect in the pessimistic scenario, and 68.88% in the optimistic scenario. If we apply those percentage increases to the spillovers generated due to the complementarity between AI and cloud computing (estimated at $ 310 per worker in 2023), we can approximate the accelerated effect that generative AI can generate on cloud-AI spillovers (Graphic 6-2).

Graphic 6-2. United States: AI spillovers with the accelerating effect of Generative AI (dollars per worker) AI spillovers with the accelerating effect of Generative AI (dollars per worker)



Source: Telecom Advisory Services analysis

This reflects the important effect that generative AI can have not only in the overall AI impact on the economy, also in the complementarity effects associated with the combined use of AI and cloud.

7. CONCLUSIONS

The purpose of this study has been to assess the economic contribution of cloud computing and evaluate the interaction benefits of enabling AI with cloud computing in the US.

The US is the most mature cloud computing market in the world, having reached US$ 361.94 billion in spending in 2023, representing 1.32% of its GDP. As in the case of cloud computing, AI spending in the US is the largest in the world, amounting to US$ 76.09 billion. In particular, spending by US enterprises in purchasing AI technology from cloud service providers in the US for 2023 amounts to US$ 6.92 billion (or 9.09% of the total AI market) and has been growing at 42.87% per year.

The economic contribution of cloud computing and cloud-enabled AI includes not only user spending, but also spillovers in terms of production efficiencies to the whole economy. The total GDP contribution of cloud in the US in 2022, comprising cloud spending and its spillovers on the economy, is sizable: US$ 404.59 billion. In addition, the contribution to GDP derived from AI as a complementary to cloud amounted to US$ 69.86 billion. Accordingly, the economic impact of cloud in the US over a ten-year timeframe (2023-2031) will reach US$ 7.87 trillion (or 2.55% of the forecasted cumulative GDP), while the impact of AI as a technology complementary to cloud will reach US$ 1. 19 trillion (or 0.39% of the forecasted cumulative GDP of the same period).

The differential economic impact across states and industries in the US was also estimated, and allowed drawing the following conclusions:

- Cloud spillovers depend on AI intensity. More precisely, for the average State, an increase of 1% in cloud adoption yields a GDP increase of 0.115%. This is equivalent to $807 million in Virginia, $1 billion in Ohio, and $4.6 billion in California.

- States that depict higher cloud adoption yield proportionally more economic gains from AI. For example, a state exhibiting 3.5% of enterprises having adopted AI combined with 30% of cloud adoption will benefit from a GDP increase of 0.52% after increasing AI adoption by 1%. The GDP impact will increase to 0.58% if cloud adoption is 50%. This additional effect generated by the increase in cloud adoption accounts to $421 million in Virginia, $544 million in Ohio, and $2.4 billion in California.

- Accordingly, states which support a more pro-active approach to cloud development, are over performing in terms of AI economic impact.

- In some industrial sectors, the main effects are linked to direct spending (professional activities, health, retail and wholesale trade, accommodation, and food), while in other sectors, the spillovers are the main source of economic impact. In some sectors, the spillovers from AI complementarity are significant (financial services and insurance, real estate, manufacturing, information industry, utilities), while in others these AI-enhancing effects are negligible due largely to low levels of AI adoption (agriculture, arts, other services).

The estimates of economic impact of cloud-enabled AI adoption presented above are mainly based on AI applications that precede generative AI. Since their launch at the end of 2022, generative AI models have moved from being "modular specialists" (generating images from captions, transcribing text to speech) to getting integrated into applications such writing assistance, coding, translation in multiple industries. Most research conducted up to date on the economic impact of generative AI refers to its potential for enhancing productivity. By adjusting the productivity estimates calculated for 2022, generative AI has the potential to generate a boost in economic benefits. Spillovers associated with cloud-AI complementarities can potentially increase from \$ 310 to \$ 353 per worker thanks to generative AI in a pessimistic scenario, and from \$ 310 to \$ 523 dollars per worker in an optimistic scenario.

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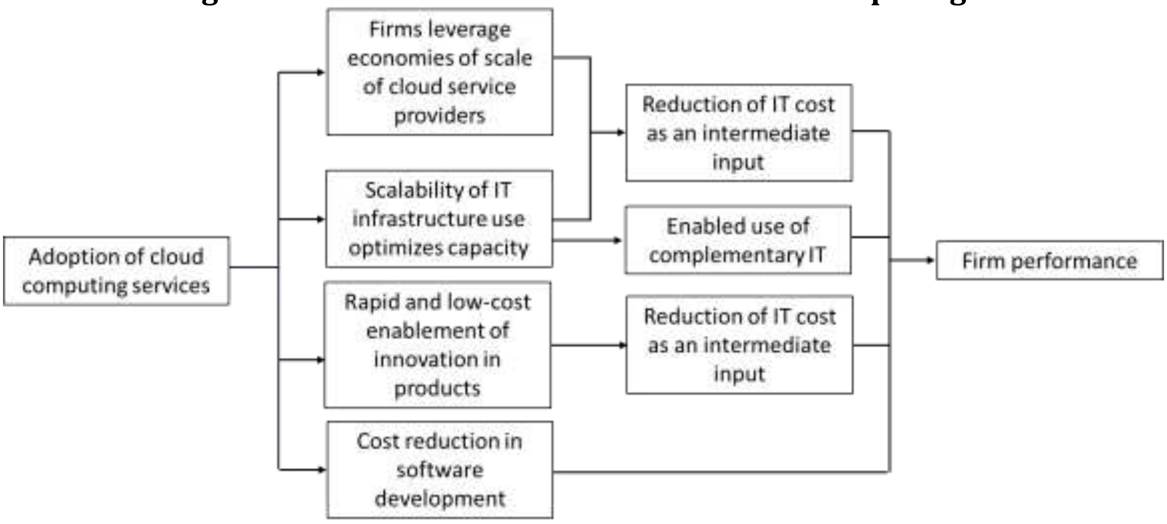
APPENDIX A. RESEARCH LITERATURE REVIEW

Three bodies of research literature have been identified as framing this study: (i) investigations of the economic impact of cloud computing; (ii) research on the contribution of AI to economic growth and productivity, and (iii) the analysis of technological complementarity between both technologies. The following review examines each area and relies on it to frame the current study hypotheses.

A.1. The economic impact of Cloud Computing

Cloud Computing is a crucial contribution to firms' digitization process, through several internal effects that can be summarized as depicted in Figure A-1.

Figure A-1. Microeconomic effects of Cloud Computing



Source: Telecom Advisory Services

Supported by cloud computing, the provision of IT-based services has experienced a significant transformation. The ability to share and access computing resources such as servers, storage areas, and network service applications remotely with high reliability and scalability is one of cloud computing's primary advantages (Park and Ryoo, 2013; Ebadi and Jafari Navimipour, 2019; Naseri and Jafari Navimipour, 2019; Khayer et al., 2020; Vu et al., 2020). Moreover, these computational resources can be accessed online at a minimal additional cost thanks to cloud technology. This means that businesses will not have to spend significant resources developing their own infrastructure.[1] As a result, firms that use cloud services can gain from advantages like cost savings, flexibility, and scalability. Businesses can also automatically scale software and storage in response to load by utilizing cloud computing, which helps them save resources (Armbrust et al., 2010). Spending less on resources improves a company's margins and, as a result, its monetary value, which is, in turn, translated into economic contribution.

[1] In the past, businesses had to build their own data centers, acquire the necessary hardware and software, and hire skilled personnel to manage them when cloud computing was not commercially available. This limited the benefits of this technology primarily to large companies.

Moreover, SaaS cloud services can have a potential impact on firm-driven ICT-enabled innovation (e.g., product development) (Chou et al., 2017; Kathuria et al., 2018; Chen et al., 2022), although the effect appears to be modest, according to some authors (Loukis et al., 2019; PWC, 2021).

Lastly, the economic impact of cloud services on software development is expected to be significant. According to Byrne et al. (2018), software development work is made easier when cloud vendors implement technologies that allow them to create products "higher up the stack" and provide services with higher abstractions. This is because companies can now concentrate solely on writing code and deploying it, which reduces development costs. This ultimately results in increased margins and possibly higher sales.

Initially, the empirical research on the economic effects of cloud computing concentrated on firm-level analysis and frequently on specific economic sectors. These studies gauged the performance of the company using a variety of factors, including financial indicators, productivity, and innovation. Schniederjans and Hales (2016) used transaction cost economics to examine how cloud computing facilitates supply chain cooperation and enhances businesses' financial and environmental performance. The authors gathered survey-based information from 247 supply chain and IT professionals, and they used structural equation modeling (SEM) to demonstrate how cloud computing can improve business performance and foster greater cooperation among supply chain participants. Similarly, Loukis et al. (2019) found that SaaS cloud technologies' operational and innovative benefits have a positive impact on business performance, leading to enhanced operations and higher rates of innovation. The study surveyed 102 Dutch firms, identifying the significance of a firm's absorptive capacity, defined as its capacity to identify, obtain, and assimilate important new knowledge from the external environment. Interestingly, Chou et al. (2017) discovered a positive correlation between cloud adoption and service innovation after analyzing data from 165 companies across a range of Taiwanese industries, including IT, travel and tourism, finance, and banking. Bolwin et al. (2022) measured the effect of AWS cloud computing on business performance through a comprehensive survey of 1,504 German companies. By extending the survey findings to all businesses, they calculated that 1.25 million German enterprises depend on the cloud, generating 11.2 billion euros in additional value growth using AWS technologies.

The goal of another research body has been to understand the factors that enhance cloud computing's influence on firm performance. Garrison et al. (2015) used SEM to analyze a survey of 302 Korean firms, determining that the impact of cloud computing on firm performance is positively influenced by managerial, technical, and relational IT capabilities, with managerial capability having the largest impact. On a global scale, Chen et al. (2022) estimated the relationship between cloud computing and firm-level performance metrics (e.g., ROA and Tobin's Q) using Difference-in-Difference econometric techniques on a world sample of firms from 2010 to 2016. Their analysis revealed a positive correlation, indicating that firms adopting cloud computing experienced significantly improved profitability and market value. The authors also identified variations in the impact of cloud computing on performance based on industry type and firm size, with manufacturing firms showing greater profitability gains after adopting cloud services compared to service firms.

Complementing the research on the economic contribution of cloud to firm performance, the focus has moved to understanding the impact at a macroeconomic level. Gal et al. (2019) estimated the impact of cloud computing (among other technologies) on multifactor productivity[2] growth for a sample of 20 European countries, applying a combination of firm-level and industry-level data to a Neo-Schumpeterian growth approach that links innovation and technology diffusion. Their results suggest that a 10-percentage point increase in adoption of cloud computing would translate into an increase in multifactor productivity growth by 0.9 percentage points. PWC (2021) studied the effects of cloud computing on productivity in Indonesia, by applying a methodology based on Yusuf (2020). Their research uses a recursive-dynamic multi-regional computable general equilibrium model and applies sector-specific labor productivity shocks to it, representing the effect of the new technological changes on the economy. Overall, they estimated that the cumulative productivity benefit to the Indonesian economy of cloud adoption will be US$ 10.7 billion over the period 2021 - 2025.

The authors of this study have produced several studies estimating the economic impact of cloud computing in the Middle East and North Africa (Katz and Jung, 2022), Sub-Saharan Africa (Katz and Jung, 2022), and Southeast Asia (Katz, Jung and Berry, 2024). All studies rely on a 3-stage least squares model incorporating cloud adoption as a term in a production function, measuring the impact on GDP growth. Cloud's contribution is verified in all studies through a positive and significant elasticity coefficient of cloud adoption ranging from 0.299 to 0.271.

A.2. The economic contribution of AI

While research on the economic effect of AI has primarily focused on the impact on labor substitution (Acemoglu and Restrepo, 2018a; 2018b; Lane and Saint-Martin, 2021; Felten, Raj, and Seamans, 2023), studies have recently started addressing the contribution to productivity. Initially, such studies have been affected by the lack of firm AI adoption data. In fact, many studies measure the use of AI among firms by relying on proxy variables, such as job postings ((Alekseeva et al., 2020, 2021; Babina et al., 2021), or patent registration data (Damioli et al., 2021; Alderucci et al., 2020.; Yang, 2022). For example, Alderucci et al. (2020) measure the intensity of AI patent grants in the US as a metric of firm AI innovation. They found that this metric is positively associated with firm growth and labor demand. Firms with high level of AI innovation appear to have 25% faster employment growth and 40% faster revenue growth than the rest of firms in the sample. A consistent conclusion is generated by Bessen and Righi (2020). The metric they rely in this case is large custom software investment and estimate that these events are associated with 7% increase in employment and 11% in revenues. While still affected by the paucity of data, other studies have emphasized innovations in their empirical approach. For example, Lu (2021) relies on a three-stage endogenous model where AI is assumed

[2] Multifactor productivity is a measure of economic performance that compares the amount of output to the amount of combined inputs, which includes labor, capital, energy, materials and purchased services.

to have the capability to accumulate through resource allocation and based on the elasticity of substitution between labor and capital. The study concludes that if the accumulation of AI leads to a rising productivity in the firms, the technology drives a positive contribution to economic growth.

More recent studies on the economic impact of AI have benefitted from the availability of data captured in national surveys. For example, Czarnitzki, Fernandez and Rammer (2022) built a classical production function incorporating AI adoption as another term and implemented an instrumental variable approach within a two-stage regression to control for endogeneity. Data on AI adoption was captured from a panel survey of German firms for 2018. In this case, the authors found positive and significant effects in the range of 6% and 4% caused by the increase of the use of AI on German firms' productivity, when measured by sales. That being said, the impact of AI on productivity based on national statistics of AI adoption has not always consistently proven to be positive. Song and Cho rely on AI adoption in Korean firms, according to Statistics Korea data for 2017 and 2018, and implement OLS and IV models. Recognizing that their approach could be limited by small sample size and endogeneity, the authors conclude that not all firms exhibit productivity improvements as a result of AI adoption although multi-plants firms appear to benefit from efficiency gains.

A.3. Technological complementarity between AI and cloud computing

The ability of cloud computing to scale IT infrastructure also makes it easier for businesses to use other cloud-enabled technologies like big data, AI machine learning, and the Internet of Things. Because these technologies allow for a fundamental transformation of business management practices, they play a significant role in some of the economic impact that digitization generates.

Despite the above-mentioned advances in the research literature, there is still a lack of analysis regarding to the role of cloud computing and its complementarity effects with other cutting-edge technologies. Cloud service providers might offer database management software, content delivery, analytics (which might include real time video and data streams analysis, and using third party data), machine learning (including deep learning inference, identifying insights and relationship in text), and security applications. Because of that, cloud computing and AI can be conceptualized as being complementary technologies.

Complementarity has been initially studied as enabler of interdependencies supporting the stimulation of demand of capital goods. This effect operates in the technology field at two levels: (i) a given technology enables the production of another one by lowering manufacturing and distribution costs (Dosi et al., 1990; Schmookler, 1966), and (ii) one technology addresses bottlenecks in the diffusion and adoption of a second one (Rosenberg, 1976). The first effect focusses on reducing the cost of intermediate inputs, while the second one addresses user needs.

The study of sector interdependencies has been extended to address the complementarity within value chains (Mäkitie et al., 2022). The authors analyze three mechanisms by which complementarity emerges: (i) **synchronization**, which depicts "the simultaneous and mutually supporting development between the input and user sectors in a technology value chain"; (ii) **amplification**, where a technology accelerates the adoption of a another one; and (iii) **integration,** whereby technological advances in one sector spill in accelerating the development and adoption of technology in another one. In particular, the principle of "amplification" is defined as follows:

> *"Diffusion of a novel technology in a user sector creates demand for products and services in the input sectors of the [technology value chain], making it imperative that input sectors are scalable enough to ensure a balance between supply and demand. Thus, economies of scale may emerge, driving further development and deployment in the user sector due to reduced costs, network effects, and increased availability of necessary services and products." (p.9)*

The case under study of complementarity between cloud computing, and AI appears to be a clear example of amplification. Each technology was developed independently, although their combination acts as a multiplier of demand and impact.

Beyond the direct impact it may generate, cloud is also expected to enable infrastructure for the use of other technologies such as AI and machine learning, which in turn, should positively influence output. This has been highlighted by Pop (2016), who argues that since machine learning is a resource-consuming task, cloud computing can provide valuable alternatives to speed-up the execution times. In turn, Omurgonulsen et al. (2021) emphasizes the increasing adoption of AI in cloud computing and the challenges associated with equipping workers with the necessary skills to make the most of it. The study also underscores the importance of ensuring enough security measures and compliance requirements before deploying cloud-based AI services.

Soni and Kumar (2022) discuss the integration of machine learning techniques in emerging cloud computing paradigms, emphasizing the study of "intelligent" AI systems. This research presents a detailed taxonomy of AI and cloud computing integration, highlighting the potential for enhanced performance through the combination of these technologies. Furthermore, Collins et al (2021) provides insights into the strategic potential of AI, emphasizing the importance of organizational resources, including technical and non-technical aspects, to fully exploit the benefits of AI. Their study also mentions the provision of infrastructure for machine learning in the cloud by large companies, such as Google, Amazon, and Microsoft, further underlining the integration of AI and cloud computing (Enholm et al, 2022). Additionally, El Khatib et al. (2019) present a case study on the integration of cloud computing with AI in the telecommunications sector, highlighting the benefits of leveraging cloud services with network function virtualization (NFV) and machine learning to improve customer experience and operational efficiency. The study emphasizes the correlation between cloud computing and AI, showcasing their interrelated nature and the support they provide to enhance agility, deploy services faster, and improve operational intelligence.

Complementarity between cloud and other technologies has already been studied by the authors of this research. In a study of economic spillovers of cloud computing in OECD countries, Katz and Jung (2024) determined empirically that the economic impact of cloud computing depends on fixed broadband adoption. To estimate cloud economic spillovers, the authors combine high speed broadband and cloud adoption in a production function estimating gross value added and productivity. The results suggest that broadband effectively enhances cloud's economic contribution. In a similar vein, Katz, Jung and Goldman (2023) studied the economic impact of cloud computing, big data and machine learning in Israeli firms. By relying on a SEM, the authors determined that cloud computing indirectly leads to more reliance on machine learning and big data applications, although the impact of these technologies on productivity is only positive and significant for large firms.

In summary, the literature review findings underscore the potential of integrating cloud computing and AI to enhance firm-level performance, emphasizing the need for skill development, security measures, and the strategic utilization of organizational resources to fully exploit the benefits of this integration. However, despite these theoretical arguments in favor of the complementary nature of both technologies, empirical research is still lacking in this field.

A.4. Conclusions of research literature review

The review of the research literature has highlighted the progress and opportunities for further development (see table A-1).

Table A-1. Research on the economic impact of cloud computing, AI and their complementarity: Progress and development of opportunities

	Progress	Development for further research
Economic impact of cloud computing	• Contribution of cloud to firm performance (productivity, product development, IT cost efficiency, profitability) • Impact of cloud on GDP growth in high- middle- and low-income economies	• Factors driving differential GDP impact of cloud within sub-sovereign geographies in high income economies
Economic impact of AI	• Impact of AI on labor substitution/creation • Link between AI adoption and firm productivity, albeit for multi-plant firms • Association between AI adoption and revenue growth	• Impact of AI on aggregate firm performance indicators (e.g., sales growth and profitability) • Impact of AI on GDP growth and productivity based on national industrial statistics
Complementarity between AI and cloud computing	• Precision in the definition of complementarity between cloud and AI (resource optimization, time required for product development) • Economic impact of cloud computing, big data and machine learning on firm performance	• Marco-economic impact of the complementarity of AI and cloud computing

In summary, this study will address the gaps in the research literature along the following objectives:

- Understand the bases of differentiated cloud economic contribution within sub-sovereign geographic entities (e.g., States)
- Base the analysis in panel data derived from reliable databases on cloud and AI adoption in enterprises
- Impact of AI on GDP growth and productivity based on national industrial statistics
- Focus the empirical strategy on exploring the complementarity between both technologies

APPENDIX B. ECONOMETRIC MODEL TO ESTIMATE CLOUD AND AI ECONOMIC IMPACT

B.1. The theoretical model

The focus of the study theoretical model is to assess (i) the economic contribution of cloud computing as a technology and (ii) the complementary economic impact of cloud computing and AI in the United States. The empirical strategy selected for this research is supported by a theoretical model that estimates spillover effects in economic output derived from cloud adoption and its potential complementarity with AI.

To estimate these effects, we start with an empirical model where output is explained through a Cobb–Douglas production function:

$$GDP_{is} = A_{is} K_{is}^{\alpha} L_{is}^{\beta} \qquad (1)$$

In equation (1), GDP represents gross domestic product, K is the physical capital stock, and L is labor. Subscripts i, and s denote, respectively, state, and economic sector. The term A represents the TFP, reflecting differences in productive efficiency across industries and states.

We expect Total Factor Productivity (TFP) to depend on cloud adoption by firms (denoted by $CLOUD$), and beyond it, we assume that higher AI use will enhance cloud impact.[3] This is reasonable, as demonstrated in the review of the literature, both technologies are complementary. As a result, TFP is proposed as:

$$A_{is} = \Omega_i \zeta_s CLOUD_{is}^{\Phi + \delta AI_{is}} \qquad (2)$$

According to it, TFP depends on state-level time-invariant characteristics represented by a fixed effect Ω_i, capturing idiosyncratic productivity effects. In addition, ζ_s reflects sector-level unobservables that make some industries more productive than others.

As it is assumed that cloud adoption contributes to increased productivity, we expect $\Phi > 0$. As another important aspect that could shape the impact of cloud on productivity is AI use, the empirical exercise will consist in identifying the sign and significance level of the parameter δ. If we verify that $\delta > 0$, this means that AI enhances the positive impact of cloud computing. Along these lines, for two states or industries with the same level of cloud adoption, we expect to observe a higher economic impact for that one with higher intensity of AI use. Inserting equation (2) into (1), we obtain:

$$GDP_{is} = \Omega_i \zeta_s CLOUD_{is}^{\Phi + \delta AI_{is}} K_{is}^{\alpha} L_{is}^{\beta} \qquad (3)$$

Applying logs to linearize, we get the final empirical specification for the output equation:

$$\log(GDP_{is}) = \mu_i + \eta_s + \alpha \log(K_{is}) + \beta\log(L_{is}) + \Phi\log(CLOUD_{is}) + \delta AI_{is}\log(CLOUD_{is})$$

where $\mu_i = \log(\Omega_i)$ is a state-level fixed effect, and $\eta_s = \log(\zeta_s)$ represents the sector unobservables. In sum, we understand that the evolution of GDP depends on some specific unobserved characteristics, on the capital stock, on labor, on cloud adoption and, on the complementary use of cloud and AI.

From the last equation, we can calculate the economic impact of cloud, which is expected to depend on the intensity of AI use:

$$\frac{\partial\log(GDP_{is})}{\partial\log(CLOUD_{is})} = \Phi + \delta AI_{is}$$

In addition, the production function can be transformed to represent productivity measures rather than overall output. Assuming constant returns to scale on capital and labour, $\alpha + \beta = 1$, output is therefore expressed as:

$$GDP_{is} = \Omega_i\zeta_s CLOUD_{is}^{\Phi+\delta AI_{is}} K_{is}^{\alpha} L_{is}^{1-\alpha}$$

Which means we can modify this equation to represent it as:

$$\left(\frac{GDP_{is}}{L_{is}}\right) = \Omega_i\zeta_s CLOUD_{is}^{\Phi+\delta AI_{is}} \left(\frac{K_{is}}{L_{is}}\right)^{\alpha}$$

So effectively, labour productivity (measured as GDP per worker) can be expressed as a function of the unobservable factors, cloud, and AI adoption, plus the physical capital stock per worker. Applying logs for linearization, we get the empirical specification for the productivity equation:

$$\log\left(\frac{GDP_{is}}{L_{is}}\right) = \mu_i + \eta_s + \alpha\log\left(\frac{K_{is}}{L_{is}}\right) + \Phi\log(CLOUD_{is}) + \delta AI_{is}\log(CLOUD_{is})$$

The estimation of the productivity equation is relevant as these different output measures explain different perspectives on firm performance: while GDP is a metric of aggregate production, labor productivity measures the value of production for the average worker, thus representing a measure of efficiency.

B.2. The dataset

The sample consists of 19 economic industrial sectors across 51 US states during the year 2018, thus representing close to 1000 observations. Data on cloud and AI variables are compiled from the Annual Business Survey (ABS) conducted by the US Census Bureau (USCB) and the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation. The survey provides information on selected economic and demographic characteristics for businesses. Included are all nonfarm employer businesses filing the 941, 944, or 1120 tax forms.

The data is compiled by combining data collected on businesses and business owners in the ABS with data collected on the economic census and administrative records. The sample is stratified by state and industry and is systematically sampled within each stratum. The ABS is conducted annually since 2017, although the technology module where questions on cloud and AI uses are addressed was not included in the post-2019 editions. This is the reason why in this study we rely on the data of the 2019 edition, based on year 2018.[4] When reporting final results, the model results will be projected through extrapolation to 2022.

The economic sectors included in the sample are detailed in Table B-1.

Table B-1. Economic sectors included in the empirical analysis

- Accommodation and food services
- Administrative and support and waste management and remediation services
- Agriculture, forestry, fishing, and hunting
- Arts, entertainment, and recreation
- Construction
- Educational services
- Finance and insurance
- Health care and social assistance
- Information
- Management of companies and enterprises
- Manufacturing
- Mining, quarrying, and oil and gas extraction
- Professional, scientific, and technical services
- Real estate and rental and leasing
- Retail trade
- Transportation and warehousing
- Utilities
- Other services

Source: Telecom Advisory Services analysis

The variables to be used in the empirical analysis are detailed in Table B-2.

Table B-2. Variables to be used in the empirical analysis

Item	Description	Source
Y	Gross Domestic Product (in current million dollars)	BEA
K	Current-cost net stock of private fixed assets (in current million dollars)	BEA
L	Total employment (number of jobs)	BEA
CLOUD	Cloud adoption, measured as enterprises using cloud-based services (every 100 enterprises). Missing values addressed through industry averages.	USCB / NCSES
CLOUD PRICE	Cloud ARPU (as a share of average revenue per firm)	Statista / BEA
CLOUD REVENUE	Cloud ARPU multiplied per the number of firms using cloud services (in current million dollars)	Statista / BEA / ABS
CLOUD PRODUCERS	Firms producing cloud-based technologies (every 100 enterprises). Missing values addressed through industry averages.	ABS
AI	AI adoption, measured as enterprises using AI services (every 100 enterprises). Missing values addressed through industry averages.	ABS
AI PRICE	AI ARPU (as a share of average revenue per firm)	Statista / BEA
AI REVENUE	AI ARPU multiplied per the number of firms using AI services (in current million dollars)	Statista / BEA / ABS
AI PRODUCERS	Firms producing AI technologies (every 100 enterprises). Missing values addressed through industry averages.	ABS

SOFTWARE	Enterprises using specialized software (every 100 enterprises). Missing values addressed through industry averages.	ABS
URBAN	Urban firms (every 100 enterprises). As data for management sector was missing, it was assumed to be equal to professional services.	ABS
STEM	Calculated as the average responses of not having STEM workers on the questions regarding technology impact on employment	ABS

Source: Telecom Advisory Services analysis

The macroeconomic variables (such as GDP, capital, and labor) are extracted from the US Bureau of Economic Analysis (BEA). In the case of the capital stock variable, BEA provides data on the current-cost net stock of private fixed assets by industries for a national level only. In order to derive state-level estimations, we followed the procedure used by Garofalo and Yamarik (2002), by prorating those industry-level values by state using the weight of each state sector GDP on the total national share for each economic sector.

Descriptive statistics are presented in Table B-3.

Table B-3. Descriptive statistics

Item	Mean	Std. Dv.
Y	18556.120	34904.310
K	49122.180	184125.200
L	182118.700	276420.400
CLOUD	34.613	14.221
CLOUD PRICE	0.023	0.020
CLOUD REVENUE	102.128	183.709
CLOUD PRODUCERS	3.283	4.492
AI	3.462	3.038
AI PRICE	0.118	0.102
AI REVENUE	55.903	106.431
AI PRODUCERS	0.403	0.724
SOFTWARE	39.346	13.832
URBAN	73.112	18.208
STEM	76.766	18.424

Source: Telecom Advisory Services analysis

Average cloud adoption level is 34.61% of firms, while the adoption of AI is much more limited, accounting only 3.46% of the surveyed firms. From an economic perspective, the average industry in an average state presents an annual output of US$ 18.56 billion, with a capital stock 2.6 times larger. Average employment is 182,000 jobs.

The AI variables to be used for the purpose of the interaction with cloud are specified as two dummies depending on the relative position of each observation in the overall distribution of AI use. From this perspective, the sample is divided into thirds. We identify a dummy variable named “AI moderate”, taking values of 1 in all cases in which the observation relies within the 33-66 percentiles interval in the distribution of the AI use variable (0 in other case). We also identity an “AI intensive” variable that takes the value of one for those observations that are located above the 66 percentiles in the distribution of the AI use variable (0 in other case). The baseline scenario, the firms with low AI use, are those situated below the 33 percentiles.

B.3. The econometric models

Two approaches were used to test the complementary economic impact of AI and cloud in the US: (i) a fixed effects OLS based on a Cobb Douglas function, and (ii) a structural model used to mitigate the reverse causality concerns resulting from simple Ordinary Least Squares (OLS) single-equation estimations.

B.3.1. Fixed effects OLS model

From an empirical viewpoint, the introduction of sector-level fixed effects in the production function presents some challenges. As the capital stock variable was built based on national sector-level data, it is not possible to introduce the 2-digit NAICS sector fixed effects. To overcome this limitation, we conducted three different approaches: first, estimation without sector level fixed effects; second, estimation with sector fixed effects defined at a higher aggregation level (agriculture, construction, industry, and services); and third, estimation with 2-digit NAICS sector fixed effects in interaction with the capital stock variable. The consider the last two approaches to be the most appropriate since controlling for sector-level unobservable factors is essential to account for heterogeneities and to avoid incurring in omitted variable biases.

Table B-4 presents the results for the fixed effects estimate of the output equation, with robust standard errors clustered at the state-level. We first assume cloud and AI to be exogenous. All estimates include state fixed effects, while for the sector level we follow the approach explained in the paragraph above. In addition, we first estimate the baseline model as presented above (columns 1-3), and then we replicate those estimates controlling by AI adoption (columns 4-6) to ensure that the complementary effects due to its interaction with cloud are being correctly identified.[5]

Table B-4. Fixed Effects estimate of output equation.

Dep. var.: log(Y)	(1)	(2)	(3)	(4)	(5)	(6)
log(K)	0.434***	0.459***	0.399***	0.440***	0.464***	0.401***
	[0.008]	[0.009]	[0.030]	[0.008]	[0.009]	[0.029]
log(L)	0.596***	0.531***	0.650***	0.600***	0.534***	0.654***
	[0.007]	[0.010]	[0.017]	[0.007]	[0.011]	[0.018]
Log (CLOUD)	0.281***	0.231***	0.140***	0.262***	0.217***	0.122***
	[0.041]	[0.042]	[0.045]	[0.041]	[0.042]	[0.044]
Log (CLOUD)#AI MODERATE	0.054***	0.068***	0.041***	0.045***	0.062***	0.031***
	[0.011]	[0.011]	[0.009]	[0.011]	[0.011]	[0.009]
Log (CLOUD)#AI INTENSIVE	0.101***	0.122***	0.079***	0.072***	0.099***	0.053***
	[0.012]	[0.012]	[0.011]	[0.013]	[0.014]	[0.011]
AI				0.023***	0.018***	0.020***
				[0.006]	[0.006]	[0.003]
State Fixed Effects	YES	YES	YES	YES	YES	YES
Sector Fixed Effects	NO	YES (aggregated)	YES (interacted)	NO	YES (aggregated)	YES (interacted)
Observations	959	959	959	959	959	959
R-squared	0.930	0.947	0.973	0.931	0.948	0.974

*Note: *** p<0.01. Robust standard errors in brackets.*
Source: Telecom Advisory Services analysis

The results for the main equation are in line with the expectations, with both physical capital and labor coefficients being positive and significant, and close to the assumption of constant returns to scale. The estimated α, that measures the share of capital returns over income, is close to the usual 1/3 typically arising from national accounts (slightly above).

In addition, cloud computing presents a positive and statistically significant direct effect on output. Also, the interaction with AI use seems to be relevant to increase the economic effects of cloud, thus validating the main hypothesis of complementarity between the two technologies of this study. In all cases, the interaction of cloud with AI intensive use presents a larger coefficient than the interaction between cloud and AI moderate use. The baseline scenario (low AI use) represents the case of lower economic impact from cloud computing.

The introduction of AI as a control reduces the coefficients associated with the interactions between AI and cloud. However, their effect remains positive and statistically significant. This will mean that the complementarity between both technologies seems to be validated.

In the Appendix we further check if these results are robust to the introduction of further control variables beyond those established in the production function as represented above. We do this to make sure that the omission of a broadband adoption regressor, due to lack of data available in the ABS, will lead to an overrepresentation of the economic effects of cloud computing and AI. We understand this is not a serious concern, as broadband is ubiquitously distributed across firms in a country as the US, which means that no big differences in adoption should be identified. In any case, by introducing the available variables in the survey that can be expected to be positively associated with broadband, we conclude that the omitted variable bias associated with broadband is not a problem in our estimate.

Next, in Table B-5 we present the results for the productivity equation. In this case, the estimates present a slightly worse, although still acceptable, model fit.

Table B-5. Fixed Effects estimate of productivity equation

Dep. var.: log(Y/L)	(1)	(2)	(3)	(4)	(5)	(6)
log(K/L)	0.420***	0.463***	0.350***	0.422***	0.465***	0.346***
	[0.005]	[0.006]	[0.017]	[0.005]	[0.006]	[0.018]
log (CLOUD)	0.267***	0.238***	0.140***	0.247***	0.218***	0.122***
	[0.039]	[0.038]	[0.045]	[0.040]	[0.039]	[0.044]
log (CLOUD)#AI MODERATE	0.059***	0.068***	0.041***	0.052***	0.062***	0.031***
	[0.010]	[0.011]	[0.009]	[0.010]	[0.011]	[0.009]
log (CLOUD)#AI INTENSIVE	0.108***	0.120***	0.079***	0.084***	0.099***	0.053***
	[0.011]	[0.012]	[0.011]	[0.012]	[0.012]	[0.011]
AI				0.020***	0.018***	0.020***
				[0.006]	[0.005]	[0.003]
State Fixed Effects	YES	YES	YES	YES	YES	YES
Sector Fixed Effects	NO	YES (aggregated)	YES (interacted)	NO	YES (aggregated)	YES (interacted)
Observations	959	959	959	959	959	959
R-squared	0.749	0.810	0.904	0.751	0.812	0.907

*Note: *** p<0.01. Robust standard errors in brackets.*
Source: Telecom Advisory Services analysis

The results verify again the economic relevance of cloud adoption to enhance productivity, and the significant role of its complementarity with AI. This means that cloud computing and AI are relevant not only to explain aggregate output, but also to drive productivity. The estimated elasticities are similar to those of the output equation.

B.3.2. Structural models

In this model, we relax the assumption of cloud and AI being exogenous. The approach to be used in this case is inspired on Roller and Waverman (2001) and Koutroumpis (2009, 2019), consisting of a structural econometric model with a production function and a supply and demand framework that endogenizes ICT related variables. To control for the concern that both cloud computing and AI may be potentially endogenous, the framework proposed by Roller and Waverman (2001) and Koutroumpis (2009, 2019) captures these two-way relationships between economic output and ICTs, by explicitly accounting for these effects in a simultaneous equations model.

To disentangle the effect of ICT-related variables on output, and its inverse, the following micromodel is formalized beyond the aggregated production equation (Table B-6).

Table B-6. System of simultaneous equations

Aggregate production equation		$Y_{is} = f(K_{is}, L_{is}, CLOUD_{is}, AI_{is})$
Cloud equations	Demand equation	$CLOUD_{is} = g(Y/L_{is}, CLOUD\ PRICE_{is}, STEM_{is}, SOFTWARE_{is}, URBAN_{is})$
	Supply equation	$CLOUD\ REVENUE_{is} = h(CLOUD\ PRICE_{is}, Y_{is}, CLOUD\ PRODUCERS_{is})$
	Cloud infrastructure production	$\Delta CLOUD_{is} = j(CLOUD\ REVENUE_{is})$
AI equations	Demand equation	$AI_{is} = k(Y/L_{is}, AI\ PRICE_{is}, STEM_{is}, SOFTWARE_{is}, URBAN_{is})$
	Supply equation	$AI\ REVENUE_{is} = v(AI\ PRICE_{is}, Y_{is}, AI\ PRODUCERS_{is})$
	AI infrastructure production	$\Delta AI_{is} = z(AI\ REVENUE_{is})$

Note: i and s denote respectively country and sector.
Source: Telecom Advisory Services

In this case, cloud demand ($CLOUD_{is}$) is expected to depend on the average income per worker (Y/L_{is}), on cloud prices ($CLOUD\ PRICE_{is}$), on the degree of human capital ($STEM_{is}$), on the degree of software use ($SOFTWARE_{is}$), and on the degree of urbanization ($URBAN_{is}$). As for the cloud supply equation, it links cloud output ($CLOUD\ REVENUE_{is}$) as a function of cloud prices ($CLOUD\ PRICE_{is}$) and the competitive intensity in the local cloud sector ($CLOUD\ PRODUCERS_{is}$). Finally, the variation in cloud adoption ($\Delta CLOUD_{is}$) is modelized to depend on cloud output ($CLOUD\ REVENUE_{is}$). A similar approach is taken for the AI-related equations.[6]

Results for the output equation are presented in Table B-7. The estimation is conducted through 3-Stage Least Squares (3SLS) simultaneous equation approach. All estimates include state level fixed effects in all equations, while all secondary equations also include sector firm effects. As for the main equation, the approach followed to account for sector level unobservable heterogeneity is similar as the one explained previously.

Table B-7. 3SLS estimate on output equation

Dep. var.: log(Y)	(1)	(2)	(3)	(4)	(5)	(6)
log(K)	0.408***	0.427***	0.401***	0.415***	0.435***	0.396***
	[0.012]	[0.011]	[0.024]	[0.012]	[0.011]	[0.024]
log(L)	0.579***	0.555***	0.633***	0.587***	0.561***	0.642***
	[0.014]	[0.014]	[0.016]	[0.014]	[0.014]	[0.016]
Log (CLOUD)	0.201***	0.292***	0.127***	0.151***	0.241***	0.079*
	[0.054]	[0.051]	[0.046]	[0.054]	[0.051]	[0.046]
Log (CLOUD)#AI MODERATE	0.060***	0.091***	0.043***	0.050***	0.079***	0.035***
	[0.011]	[0.010]	[0.008]	[0.011]	[0.010]	[0.008]
Log (CLOUD)#AI INTENSIVE	0.133***	0.160***	0.097***	0.089***	0.117***	0.068***
	[0.013]	[0.011]	[0.008]	[0.015]	[0.013]	[0.009]
AI				0.041***	0.039***	0.031***
				[0.007]	[0.006]	[0.004]
Dep. var.: log (CLOUD)						
Log (CLOUD PRICE)	-0.025*	-0.026*	-0.031**	-0.026*	-0.027*	-0.031**
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
Log (Y/L)	-0.008	-0.008	-0.016	-0.008	-0.008	-0.016
	[0.022]	[0.021]	[0.022]	[0.022]	[0.022]	[0.022]
Log (SOFTWARE)	0.150***	0.150***	0.151***	0.150***	0.150***	0.151***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
Log (URBAN)	0.034	0.034	0.038	0.035	0.034	0.038
	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]
Log (STEM)	-0.003	-0.003	0.001	-0.003	-0.003	0.001
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
Dep. var.: log (CLOUD REVENUE)						
Log (CLOUD PRICE)	0.960***	0.959***	0.958***	0.957***	0.956***	0.955***

	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
log(Y)	0.978***	0.979***	0.979***	0.975***	0.976***	0.976***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
CLOUD PRODUCERS	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Dep. var.: log(ΔCLOUD)						
Log (CLOUD REVENUE)	0.070***	0.070***	0.079***	0.072***	0.072***	0.081***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Dep. var.: log (AI)						
Log (AI PRICE)	-0.060***	-0.066***	-0.074***	-0.088***	-0.096***	-0.100***
	[0.020]	[0.020]	[0.021]	[0.025]	[0.025]	[0.025]
log(Y/L)	0.029**	0.027*	0.031**	0.028*	0.027*	0.036**
	[0.014]	[0.014]	[0.014]	[0.015]	[0.015]	[0.015]
Log (SOFTWARE)	0.008	0.008	0.008	0.006	0.006	0.006
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Log (URBAN)	-0.004	-0.004	-0.004	-0.005	-0.005	-0.008
	[0.022]	[0.022]	[0.022]	[0.023]	[0.023]	[0.023]
Log (STEM)	-0.017	-0.017	-0.017	-0.011	-0.011	0.006
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.010]
Dep. var.: log (AI REVENUE)						
Log (AI PRICE)	1.011***	1.006***	1.000***	0.983***	0.976***	0.973***
	[0.019]	[0.018]	[0.019]	[0.023]	[0.022]	[0.023]
log(Y)	1.073***	1.072***	1.075***	1.073***	1.073***	1.076***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
AI PRODUCERS	-0.002	-0.003	-0.001	0.000	-0.001	0.001
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Dep. var.: log(ΔAI)						
Log (AI REVENUE)	0.326***	0.325***	0.339***	0.413***	0.411***	0.421***
	[0.006]	[0.006]	[0.005]	[0.006]	[0.006]	[0.006]
State Fixed Effects (all equations)	YES	YES	YES	YES	YES	YES
Sector Fixed Effects (output equation)	NO	YES (aggregated)	YES (interacted)	NO	YES (aggregated)	YES (interacted)
Sector Fixed Effects (remaining equations)	YES	YES	YES	YES	YES	YES
Observations	878	878	878	878	878	878
R-squared (output equation)	0.924	0.939	0.974	0.924	0.939	0.974

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets.*
Source: Telecom Advisory Services analysis

In columns 1-3 of Table B-7 we estimate the model as presented in the theoretical model and presented above, while in columns 4-6 we introduce the AI control. The results for the main equation are in line with the expectations, with cloud computing presenting a positive and significant effect across all estimates. Only in the estimation reported in column 6 the coefficient loses some magnitude and significance, although it remains statistically different from zero at a 10% level. AI use (in interaction with cloud) presents a positive and highly significant coefficient (at 1% level), suggesting that it is effectively enhancing the economic effects of cloud computing.

According to the econometric estimations, **a 1% increase in cloud adoption is associated with an increase of 0.079% of the GDP, regardless of the level of AI use**. Considering the 2023 US GDP estimated by the International Monetary Fund (IMF), **this effect accounts for $21.29 billion. For those observations with moderate AI use, the elasticity increases to 0.114% (equivalent to $ 30.72 billion,** resulting from adding the baseline coefficient of 0.079 plus the effect associated to the AI MODERATE variable, 0.035), **while in cases of intensive AI use the elasticity yields 0.147% (equivalent to $ 39.62 billion,** resulting from the coefficient 0.079 plus the effect associated to the AI INTENSIVE variable, 0.068).

As for the remaining equations, results are in line with the expectations. Particularly, cloud demand depends positively on the degree of firm's specialized software use, while it depends negatively on the service price. The coefficient for income per worker is not significant, suggesting demand insensitiveness to income differentials. In addition, both income and prices drive positively cloud revenue, as reflected in the supply equation. On the other hand, the larger the expenditure in cloud, the bigger the variation of adoption levels with respect to the respective state average, as expected.

As for the AI-related equations, demand seems to depend positively on firm's income per worker, while the coefficient for price is negative and significant. The fact that AI demand depends positively on firm's income means that the suspected reverse causality is effectively taking place, and thus, controlling for endogeneity seems necessary. As for AI revenue, it depends positively on prices and income. Finally, the larger the expenditure in AI, the bigger the variation of adoption levels with respect to the respective state average, as expected.

In Table B-8 we turn to the labor productivity estimate. The estimated α remains almost unchanged with respect to the previous estimations. As expected, labor productivity depends positively on both cloud and AI, while the complementarity between both technologies again generates positive economic spillovers. No major changes arise in the secondary equations of the model.

Table B-8. 3SLS estimate on productivity equation

Dep. var.: log(Y/L)	(1)	(2)	(3)	(4)	(5)	(6)
log(K/L)	0.413***	0.433***	0.367***	0.414***	0.436***	0.358***
	[0.010]	[0.009]	[0.016]	[0.010]	[0.009]	[0.016]
Log (CLOUD)	0.210***	0.313***	0.127***	0.144***	0.244***	0.079*
	[0.051]	[0.048]	[0.046]	[0.052]	[0.049]	[0.046]
Log (CLOUD)#AI MODERATE	0.058***	0.089***	0.043***	0.051***	0.079***	0.035***
	[0.011]	[0.010]	[0.008]	[0.011]	[0.010]	[0.008]
Log (CLOUD)#AI INTENSIVE	0.131***	0.156***	0.097***	0.090***	0.116***	0.068***
	[0.012]	[0.011]	[0.008]	[0.014]	[0.012]	[0.009]
AI				0.042***	0.039***	0.031***
				[0.007]	[0.006]	[0.004]
Dep. var.: log (CLOUD)						
Log (CLOUD PRICE)	-0.025*	-0.026*	-0.031**	-0.026*	-0.027*	-0.031**
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
log(Y/L)	-0.008	-0.008	-0.016	-0.008	-0.009	-0.016
	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
Log (SOFTWARE)	0.150***	0.150***	0.151***	0.150***	0.150***	0.151***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]	[0.016]
Log (URBAN)	0.034	0.034	0.038	0.035	0.034	0.038
	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]	[0.035]
Log (STEM)	-0.003	-0.003	0.001	-0.003	-0.003	0.001
	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]	[0.019]
Dep. var.: log (CLOUD REVENUE)						
Log (CLOUD PRICE)	0.960***	0.959***	0.958***	0.957***	0.956***	0.955***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
log(Y)	0.978***	0.979***	0.979***	0.975***	0.976***	0.976***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
CLOUD PRODUCERS	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Dep. var.: log(ΔCLOUD)						
Log (CLOUD REVENUE)	0.070***	0.070***	0.079***	0.072***	0.072***	0.081***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Dep. var.: log (AI)						

Log (AI PRICE)	-0.059***	-0.065***	-0.074***	-0.087***	-0.096***	-0.100***
	[0.020]	[0.020]	[0.021]	[0.025]	[0.025]	[0.025]
log(Y/L)	0.028**	0.027*	0.031**	0.027*	0.027*	0.036**
	[0.014]	[0.014]	[0.014]	[0.015]	[0.015]	[0.015]
Log (SOFTWARE)	0.008	0.008	0.008	0.006	0.006	0.006
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Log (URBAN)	-0.003	-0.004	-0.004	-0.005	-0.005	-0.008
	[0.022]	[0.022]	[0.022]	[0.023]	[0.023]	[0.023]
Log (STEM)	-0.017	-0.017	-0.017	-0.011	-0.011	-0.015
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
Dep. var.: log (AI REVENUE)						
Log (AI PRICE)	1.011***	1.006***	1.000***	0.985***	0.977***	0.973***
	[0.019]	[0.018]	[0.019]	[0.023]	[0.023]	[0.023]
log(Y)	1.073***	1.072***	1.075***	1.073***	1.073***	1.076***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
AI PRODUCERS	-0.002	-0.003	-0.001	0.000	-0.001	0.001
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Dep. var.: log(ΔAI)						
log(AI REVENUE)	0.326***	0.325***	0.339***	0.413***	0.411***	0.421***
	[0.006]	[0.006]	[0.005]	[0.006]	[0.006]	[0.006]
State Fixed Effects (all equations)	YES	YES	YES	YES	YES	YES
Sector Fixed Effects (productivity equation)	NO	YES (aggregated)	YES (interacted)	NO	YES (aggregated)	YES (interacted)
Sector Fixed Effects (remaining equations)	YES	YES	YES	YES	YES	YES
Observations	878	878	878	878	878	878
R-squared (productivity equation)	0.749	0.798	0.914	0.748	0.797	0.913

*Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in brackets.*
Source: Telecom Advisory Services analysis

The results presented above provide robust evidence of the significant effect that cloud computing has on economic output and productivity levels. In addition, results are clear in pointing out to the complementarities of cloud with AI technology. Clearly, the results suggest that AI plays an enhancing effect over cloud computing economic impact. This is explained because cloud is an enabler-technology, meaning that its economic effects are maximized when used to leverage other technologies such as AI. In addition, AI to be successful requires the presence of sound cloud computing services, meaning that firms adopting AI solutions without a solid cloud infrastructure will not be able to make the most out of this technology. The coefficients generated in the econometric specified in this chapter will be used to calculate the economic contribution of cloud as well as that of cloud as complementary with AI for 2022.

B.3.3 Further control variables

In our baseline equation estimated, a potential risk that arises from introducing only CLOUD and AI as ICT-related variables is the possibility of incurring in omitted variable bias, as these indicators may be absorbing the effects of other digitization measures. In other words, the contribution of cloud computing would capture the effects of other digital technologies, such as broadband, which needs to be isolated.

Typically, these production functions are estimated with a measure of broadband adoption to control for the different degrees of digitalization across economic units, however, data is not available in the ABS at the industry-state level. Introducing values determined at the state-level only is not an option as they will be collinear with the state fixed effects.

In order to check if this omission may be biasing our results, we conducted some robustness checks introducing further controls that are expected to correlate with broadband adoption and at the same time are expected to be related with CLOUD and AI. The only available metrics in the ABS are those related to share of adoption of specialized software and specialize equipment. Table B-9 reports the main results of re-estimating the main findings, now including these further controls.

Table B-9. Fixed Effects estimate of output equation – with further controls

Dep. var.: log(Y)	(1)	(2)	(3)	(4)
log(K)	0.468***	0.401***	0.470***	0.400***
	[0.009]	[0.030]	[0.009]	[0.029]
log(L)	0.539***	0.652***	0.541***	0.655***
	[0.011]	[0.019]	[0.011]	[0.020]
log(CLOUD)	0.238***	0.161***	0.229***	0.149***
	[0.059]	[0.057]	[0.058]	[0.055]
log(CLOUD)#AI MODERATE	0.069***	0.040***	0.064***	0.031***
	[0.011]	[0.009]	[0.012]	[0.009]
log(CLOUD)#AI INTENSIVE	0.125***	0.077***	0.107***	0.053***
	[0.012]	[0.011]	[0.015]	[0.011]
AI			0.013**	0.019***
			[0.006]	[0.003]
log(EQUIPMENT)	0.104***	0.056**	0.094***	0.038*
	[0.020]	[0.024]	[0.020]	[0.021]
log(SOFTWARE)	-0.031	-0.043	-0.031	-0.044
	[0.056]	[0.045]	[0.055]	[0.044]
State Fixed Effects	YES	YES	YES	YES
Sector Fixed Effects	YES (aggregated)	YES (interacted)	YES (aggregated)	YES (interacted)
Observations	952	952	952	952
R-squared	0.947	0.973	0.947	0.974

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets.*
Source: Telecom Advisory Services analysis

While the equipment variable appears to be relevant to capture some omitted heterogeneity in explaining output (presents a positive and significant coefficient), the software variable is not statistically significant. More important for our purposes, the presence of these variables do not affect the coefficients associated to cloud and its interaction with AI. Moreover, they seem to increase in magnitude, suggesting that the omission of digital variables does not seem to be generating an upward bias in our main estimations.