

Telecom Advisory Services

WORLD ECONOMIC IMPACT OF **CLOUD COMPUTING AND ARTIFICIAL INTELLIGENCE**



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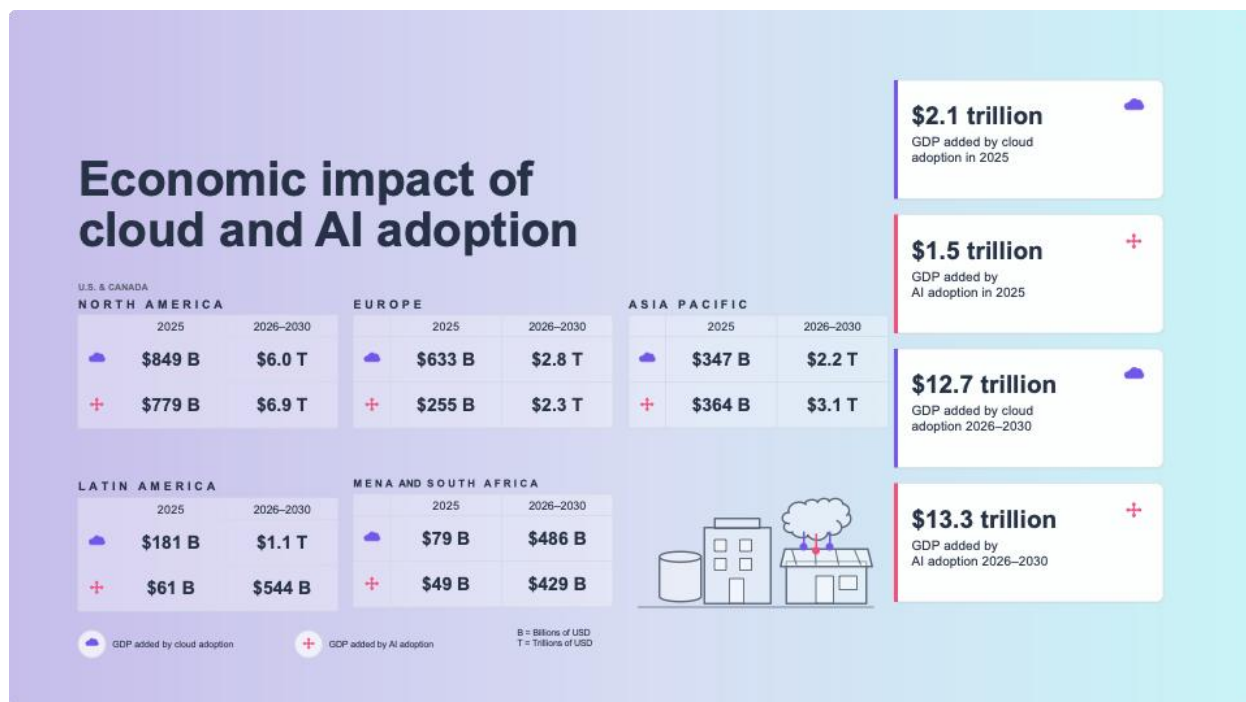
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ESTIMATING THE WORLD ECONOMIC IMPACT OF CLOUD COMPUTING AND ARTIFICIAL INTELLIGENCE



Telecom Advisory Services LLC conducted our first worldwide assessment of the economic value of cloud computing and artificial intelligence (AI) in 2024. This assessment concluded that in 2023 cloud computing contributed US\$ 1.04 trillion, while the cloud-enabled AI (defined as AI revenues generated by cloud service providers) generated US\$ 98.8 billion.¹ Since then, the digital ecosystem has dramatically changed, driven first and foremost by the explosion in the use of AI. This has led us to assess the economic impact of AI not in terms of the revenues offered by cloud service providers only, but also by all suppliers ranging from AI labs to systems integrators and new players in the infrastructure portion of the AI value chain, such as AI factories and “neoclouds”. In sum, our new estimation of economic value addresses the total contribution of AI and captures the extraordinary growth undergoing the industry. As in the prior study, the analysis includes not only the GDP contribution of spending in cloud computing and AI but also measures the impact of such technologies on IT cost efficiencies, productivity, and innovation, labeled as spillovers.²

Two methodological considerations are important when interpreting these estimates. First, the coefficients used to calculate spillovers were estimated from datasets whose reference periods vary by region and technology. The Cloud models use regional samples dated between 2016 and 2023, including a 2018 U.S. cross-section and a 2021 European cross-

¹ See Katz, R. and Jung, J. (2024). *Economic impact of cloud computing and artificial intelligence*. Reports by region in <https://www.teleadv.com/economic-impact-of-cloud-computing-and-artificial-intelligence/>

² The methodology and models relied upon to estimating the spillovers are included in the Appendices of this document.

section, while the AI model uses a 26-country panel covering 2019–2023. Although the market-size, spending, and forecast inputs used to scale the 2025 estimates were updated wherever newer information was available, the estimated relationships may not fully reflect the capabilities and adoption patterns of Cloud and AI in 2025.

Second, our goal has been to provide estimates that could be attributed causal interpretations rather than mere correlations. The Cloud impact analysis uses a three-stage least squares system composed of four equations that jointly model economic output, cloud demand, supplier revenue, and infrastructure production. This model structure explicitly recognizes that stronger economies may adopt more Cloud services and is designed to reduce the endogeneity bias that would affect a single-equation regression. The AI impact analysis estimates a structured production function and addresses endogeneity through the Generalized Method of Moments, a methodology used to measure the economic impact of a particular variable as AI spending in economic output. It uses countries’ historical AI-related academic research activity as an instrument, together with country and year fixed effects. Both approaches seek to isolate the effect of technology adoption from pre-existing differences across economies and from the possibility that higher GDP itself drives technology adoption. The estimates remain conditional on the validity of the model specifications and instruments.

This study’s overarching conclusion is that cloud computing, as a stand-alone technology, contributed US\$ 2.1 trillion to the 2025 world’s GDP between technology spending and spillovers, while AI’s economic impact reached US\$ 1.5 trillion (the sum of both represents 3.28% of output of the countries analyzed) (see table A).³

Table A. Economic impact of cloud and AI adoption (in US\$) (2025)

Region	Cloud computing	Artificial Intelligence
North America (United States, Canada)	\$ 849 B	\$ 779 B
Europe (Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom)	\$ 633 B	\$ 255 B
Asia Pacific (Australia, Bangladesh, China, India, Indonesia, Japan, Korea, Malaysia, N. Zealand, Pakistan, Philippines, Singapore, Thailand, Viet Nam)	\$ 347 B	\$ 364 B
Latin America (Argentina, Bolivia, Brazil, Chile, Colombia, D. Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay)	\$ 181 B	\$ 61 B
Middle East, North Africa and South Africa (Algeria, Bahrain, Egypt, Israel, Jordan, Kuwait, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, Turkey, UAE, South Africa)	\$ 79 B	\$ 49 B
TOTAL	\$ 2,089 B	\$ 1,508 B

Sources: IDC (2024). *IDC’s Worldwide Software and Public Cloud Services Spending Guide (July V2 2024)*. IDC (2025). *Worldwide AI and Generative AI Spending Guide – Forecast 2025 (August V2 2025)*; Telecom Advisory Services analysis.

³ Detailed economic impact by country for 2025 is included in Appendix E.

The breakdown between spending and spillovers by region provides a comparative perspective of the different stages of development of cloud computing and AI (see table B).

Table B. Economic impact of cloud and AI adoption (in US\$) (2025)

Region	Cloud computing			Artificial Intelligence		
	Spending	Spillovers	Total	Spending	Spillovers	Total
North America	\$756 B	\$ 93 B	\$ 849 B	\$ 442 B	\$ 337 B	\$ 779 B
Europe	\$ 325 B	\$ 308 B	\$ 633 B	\$ 89 B	\$ 166 B	\$ 255 B
Asia Pacific	\$ 226 B	\$ 121 B	\$ 347 B	\$ 116 B	\$ 248 B	\$ 364 B
Latin America	\$ 48 B	\$ 133 B	\$ 181 B	\$ 11 B	\$ 50 B	\$ 61 B
Middle East, North Africa and South Africa	\$ 31 B	\$ 48 B	\$ 79 B	\$ 8 B	\$ 41 B	\$ 49 B
TOTAL	\$ 1,386	\$ 703	\$ 2,089 B	\$ 606	\$ 842	\$ 1,508 B

Sources: IDC (2024). *IDC's Worldwide Software and Public Cloud Services Spending Guide (July V2 2024)*. IDC (2025). *Worldwide AI and Generative AI Spending Guide – Forecast 2025 (August V2 2025)*; Telecom Advisory Services analysis.

As a relatively more mature technology, the spillovers of cloud computing represent a lower portion of total economic effect than those of artificial intelligence (34% vs. 56%).

The study also measures the cumulative impact of both technologies between 2026 and 2030, factoring in the extraordinary growth in AI adoption going forward. In this regard, this study's conclusion is that cloud computing, will contribute US\$ 12.7 trillion to the world's GDP between 2026 and 2030, while AI's economic impact will reached US\$ 13.3 trillion within the same timeframe. (see table C).

Table C. Economic impact of cloud and AI adoption (in US\$) (2026-2030)

Region	Cloud computing	Artificial Intelligence
North America	\$ 6.04 T	\$ 6.93 T
Europe	\$ 2.78 T	\$ 2.29 T
Asia Pacific	\$ 2.25 T	\$ 3.07 T
Latin America	\$ 1.15 T	\$ 0.54 T
Middle East, North Africa and South Africa	\$ 0.49 T	\$ 0.43 T
TOTAL	\$ 12.71 T	\$ 13.26 T

Sources: IDC (2024). *IDC's Worldwide Software and Public Cloud Services Spending Guide (July V2 2024)*. IDC (2025). *Worldwide AI and Generative AI Spending Guide – Forecast 2025 (August V2 2025)*; Telecom Advisory Services analysis.

In conclusion, given the important economic impact of cloud and AI, countries have the opportunity to accelerate their development, thereby increasing their output.

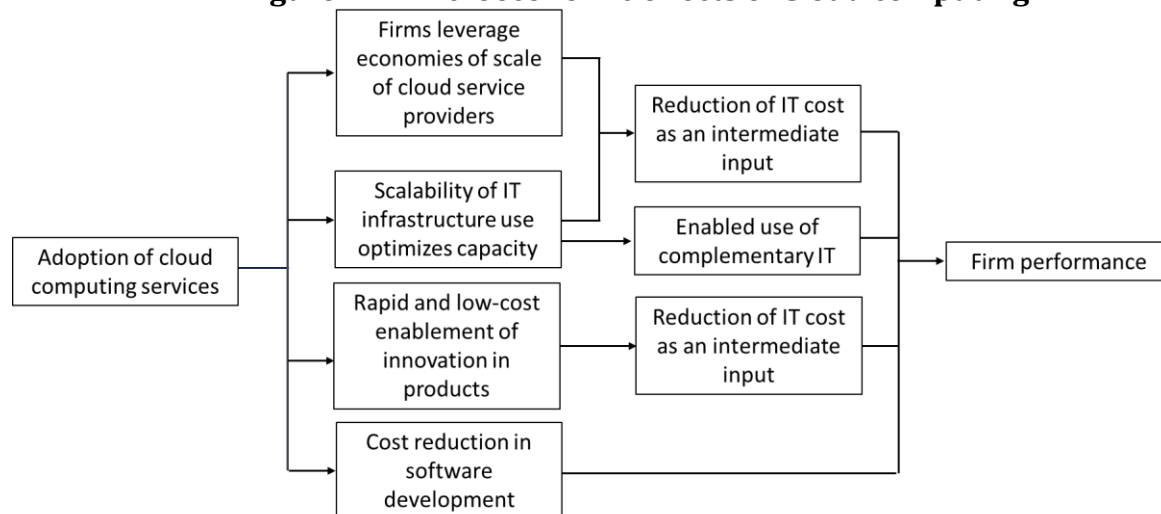
A. RESEARCH LITERATURE REVIEW

Two bodies of research literature frame this study: (i) investigations of the economic impact of Cloud computing; and (ii) research on the contribution of artificial intelligence (AI) to economic growth and productivity. The review below summarizes both strands and establishes the basis for the two separate empirical models used in the study.

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.⁴ 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.

⁴ 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 enterprise 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 productivity⁵ 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 three-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 0.271 to 0.299.

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

⁵ Multifactor productivity is a measure of economic performance that compares the amount of output to the number of combined inputs, which includes labor, capital, energy, materials and purchased services.

a three-stage endogenous model where AI is assumed 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. Conclusions of the 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 and AI: progress and opportunities for further research

	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

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

- Understand the basis of differentiated Cloud economic contributions across the six study regions.
- Base the analysis on reliable and traceable databases for Cloud revenues, AI spending, and macroeconomic activity.
- Estimate the impact of AI spending growth on GDP and productivity through a common international model.

B. ECONOMETRIC MODEL TO ESTIMATE CLOUD ECONOMIC IMPACT

B.1. The theoretical model

The focus of this chapter is to estimate the standalone economic contribution of Cloud computing. AI variables are included as controls and, where available, as interaction terms so that AI-related effects are not double counted in the Cloud estimate; the independent contribution of AI is addressed in Chapter C. The same theoretical structure is estimated separately for the six study regions—the United States, Canada, Europe, Asia-Pacific, Latin America, and MENA, South Africa and Türkiye—using the most appropriate regional unit of observation. We start with an empirical model in which output is explained through a Cobb–Douglas production function:

$$GVA_{is} = A_{is} K_{is}^{\alpha} L_{is}^{\beta} \quad (1)$$

In equation (1), GVA represents gross value added, K is the physical capital stock, and L is labor. Subscripts i , and s denote, respectively, country, and economic sector. The term A represents the Total Factor Productivity (TFP), reflecting differences in productive efficiency across industries and countries.

We allow TFP to depend on Cloud enterprise adoption (denoted by $CLOUD$) and include an AI term and, where supported by the regional data, a Cloud–AI interaction. The interaction is an empirical control: its sign and statistical significance are estimated rather than assumed. TFP is therefore proposed as:

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

Accordingly, TFP depends on region-appropriate time-invariant fixed effects that capture idiosyncratic productivity differences. The model also incorporates sector fixed effects when sectoral observations are available, or time effects and controls in the country-panel specifications.

Cloud enterprise adoption is expected to contribute positively to productivity, so we expect $\Phi > 0$. The parameter δ captures any incremental association between the Cloud term and AI intensity. Estimating both parameters makes it possible to isolate the baseline Cloud effect while treating any additional AI-related association separately. Inserting equation (2) into (1), we obtain:

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

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

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

where the fixed effects represent the relevant country, state, sector, and/or time dimensions of each regional dataset. In sum, the evolution of output depends on unobserved regional characteristics, capital, labor, Cloud adoption, and the AI controls supported by the sample.

From the last equation, we calculate the standalone economic impact of Cloud using the baseline Cloud coefficient. Interaction terms are retained for model identification and sensitivity analysis but are not added to the separately estimated AI contribution.

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

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

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

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

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

So effectively, labor productivity (measured as GVA 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:

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

The productivity equation provides a complementary measure of performance: GVA or GDP captures aggregate production, while labor productivity captures value added per worker. Across the six regional estimations, the output equation supplies the Cloud elasticity used for the economic-impact calculation, with the precise unit of observation and controls adapted to each regional dataset.

The contribution of Cloud to output is estimated through the parameter Φ in the output equation: a 1% increase in the Cloud adoption/quality driver yields an increase in output of $\Phi\%$. The corresponding productivity specification provides a robustness check. Any Cloud–AI interaction is interpreted separately from the baseline Cloud coefficient to avoid double counting with Chapter C.

The same separation is maintained in the productivity specification: the baseline Cloud term measures the standalone Cloud association, while AI-related terms are controls and are not added to the Cloud spillover reported in the final results.

B.2. The dataset

The Cloud model is estimated separately for each of the six study regions. Three regional models use sectoral data (the United States, Canada, and Europe), while the Asia-Pacific, Latin American, and MENA models use country panels. This preserves the common production-function and simultaneous-equation logic while allowing each model to use the most reliable unit of observation available in the regional source data.

Table B-1. Regional estimation samples

Region	Unit of observation	Reference period	Coverage
United States	State × industry	2018	51 states; 19 industries
Canada	Industry × year	2019–2021	84 industries
Europe	Country × sector	2021	26 countries; 9 sectors (*)
Asia-Pacific	Country × year	2016–2023	16 countries
Latin America	Country × year	2016–2022	16 countries
MENA, South Africa and Türkiye	Country × year	2017–2023	13 countries

(*) The nine sectors constitute the European estimation sample for which harmonized country-sector information was available across the variables required by the model. They include the principal market activities covered by the underlying databases, but they should not be interpreted as an exhaustive decomposition of GDP.

Source: *Telecom Advisory Services analysis*

The variables used in the six regional econometric models are detailed in Table B-2. The Item and Description columns harmonize variables that have equivalent functions across the regional specifications, while the Source column identifies the database used in each region. National statistical agencies are used whenever sectoral observations are available, and internationally comparable sources are used for the country panels.

Table B-2. Variables used in the regional Cloud econometric models

Item	Description	Source
OUTPUT (Y / VA)	Gross domestic product, gross value added, or sectoral value added, according to the unit of observation used in each model.	United States: BEA Canada: Statistics Canada Europe: Eurostat Asia-Pacific: PWT / IMF Latin America: PWT / IMF MENA, South Africa and Türkiye: PWT / IMF
CAPITAL (K)	Current-cost or constant-price stock of fixed assets and physical capital.	United States: BEA Canada: Statistics Canada Europe: Eurostat Asia-Pacific: PWT / IMF Latin America: PWT / IMF MENA, South Africa and Türkiye: PWT / IMF
LABOR (L)	Employment measured as jobs, employed persons, or millions of people employed.	United States: BEA Canada: Statistics Canada Europe: Eurostat Asia-Pacific: PWT / World Bank Latin America: PWT / World Bank MENA, South Africa and Türkiye: PWT / World Bank

Item	Description	Source
CLOUD	Enterprise or company adoption of Cloud computing services; regional estimates are used where official adoption data are unavailable. ⁶	United States: US Census Bureau / NCSES Canada: Statistics Canada Europe: Eurostat Asia-Pacific: regional adoption estimates Latin America: regional adoption estimates MENA, South Africa and Türkiye: regional adoption estimates
CLOUD PRICE / COST	Cloud ARPU relative to firm revenue, or a communications-cost indicator used in the Cloud demand equation.	United States: Statista / BEA Canada: TeleGeography / Statistics Canada Europe: Statista / Eurostat Asia-Pacific: TeleGeography Latin America: TeleGeography MENA, South Africa and Türkiye: TeleGeography United States: Statista / BEA / Annual Business Survey
CLOUD REVENUE	Revenue generated by Cloud services, or Cloud ARPU multiplied by the number of adopting firms.	Canada: IDC / Statistics Canada Europe: Statista / Eurostat Asia-Pacific: IDC / Statista Latin America: IDC / Statista MENA, South Africa and Türkiye: IDC / Statista United States: Annual Business Survey
CLOUD PRODUCERS	Number or prevalence of firms supplying Cloud services.	Canada: Statistics Canada / Crunchbase / TAS Europe: Crunchbase / TAS Asia-Pacific: Crunchbase / TAS Latin America: Crunchbase / TAS MENA, South Africa and Türkiye: Crunchbase / TAS United States: Annual Business Survey
AI	Enterprise AI adoption or estimated AI use; included as a control in the Cloud specification where supported by the sample.	Canada: Statistics Canada Europe: Eurostat Asia-Pacific: regional AI adoption estimates Latin America: regional AI adoption estimates MENA, South Africa and Türkiye: regional AI adoption estimates United States: Statista / BEA
AI PRICE / ARPU	AI ARPU relative to firm revenue or the price indicator used in the AI demand equation.	Canada: Statista / Statistics Canada Europe: Statista / Eurostat Asia-Pacific: Statista / TAS Latin America: Statista / TAS MENA, South Africa and Türkiye: Statista / TAS United States: Statista / BEA / Annual Business Survey
AI REVENUE	Revenue generated by AI services, or AI ARPU multiplied by the number of adopting firms.	Canada: Statista / Statistics Canada Europe: Statista / Eurostat Asia-Pacific: Statista / TAS Latin America: Statista / TAS MENA, South Africa and Türkiye: Statista / TAS

⁶ The model to estimate cloud adoption for Latin America, Asia Pacific and MENA consists of using this variable as dependent, and cloud expenditure per capita, GDP per capita and the number of companies in the cloud per 1 million inhabitants as explanatory variables. Cloud adoption values are drawn from the OECD statistics dataset. Cloud spending per capita was calculated from IDC spending data, while the number of cloud companies per million citizens comes from Crunchbase (see, as an example, Katz, R. and Jung, R. (2024). Economic impact of cloud computing and artificial intelligence in Latin America, Appendix C.

Item	Description	Source
AI PRODUCERS	Number or prevalence of firms supplying AI technologies and services.	United States: Annual Business Survey Canada: Statistics Canada / Crunchbase / TAS Europe: Crunchbase / TAS Asia-Pacific: Crunchbase / TAS Latin America: Crunchbase / TAS MENA, South Africa and Türkiye: Crunchbase / TAS
SOFTWARE CONTROLS	Use of specialized software, enterprise resource planning (ERP), or customer relationship management (CRM) tools.	United States: Annual Business Survey Canada: Statistics Canada Europe: Eurostat Asia-Pacific: not separately included Latin America: not separately included MENA, South Africa and Türkiye: not separately included
URBAN	Urban population or urban-firm indicator used as a demand or structural control.	United States: Annual Business Survey Canada: Statistics Canada regional firm distribution Europe: World Bank Asia-Pacific: World Bank Latin America: World Bank MENA, South Africa and Türkiye: World Bank
HUMAN CAPITAL	ICT specialists, STEM availability, schooling, or tertiary-education indicators.	United States: Annual Business Survey Canada: Statistics Canada / OECD Europe: Eurostat Asia-Pacific: UNESCO / TAS Latin America: UNESCO MENA, South Africa and Türkiye: UNESCO / TAS
OTHER REGIONAL CONTROLS	Additional controls included only where relevant to the corresponding regional specification.	United States: Annual Business Survey Canada: Statistics Canada / TeleGeography / OECD Europe: Eurostat / World Bank Asia-Pacific: regional model controls Latin America: Ookla broadband speed MENA, South Africa and Türkiye: Our World in Data oil price

Source: Telecom Advisory Services analysis

B.3. Econometric models

The common structural approach follows Röllér and Waverman (2001) and Koutroumpis (2009, 2019). A production equation is estimated jointly with Cloud demand, Cloud supply, and Cloud infrastructure-production equations. The system is estimated by three-stage least squares (3SLS), which treats Cloud adoption and output as jointly determined and reduces the reverse-causality bias that would arise in a single-equation ordinary least squares model. The same system is re-estimated for each region using the dataset and controls summarized in Section B.2.

Table B-3. System of simultaneous equations estimated in each region

Aggregate production equation		$Y_{is} = f(K_{is}, L_{is}, CLOUD_{is}, AI_{is})$
Cloud equations	Demand equation	$CLOUD_{is} = g(Y_{is}, CLOUD\ PRICE_{is}, HK_{is}, SOFTWARE_{is}, URBAN_{is})$
	Supply equation	$CLOUD\ REVENUE_{is} = h(CLOUD\ PRICE_{is}, Y_{is}, CLOUD\ COMP_{is})$

	Cloud infrastructure production	$\Delta \text{CLOUD}_{is} = j(\text{CLOUD REVENUE}_{is})$
AI equations	Demand equation	$\text{AI}_{is} = k(Y/\text{FIRM}_{is}, \text{AI PRICE}_{is}, \text{HK}_{is}, \text{SOFTWARE}_{is}, \text{URBAN}_{is})$
	Supply equation	$\text{AI REVENUE}_{is} = v(\text{AI PRICE}_{is}, Y_{is}, \text{AI COMP}_{is})$
	AI infrastructure production	$\Delta \text{AI}_{is} = z(\text{AI REVENUE}_{is})$

Note: i identifies the regional unit of observation (state, industry, country, or sector) and t identifies time where a panel is available.

Source: Telecom Advisory Services analysis

Table B-4 reports the complete 3SLS simultaneous-equation results for the six regional Cloud models. Each regional column presents the output specification used to characterize that region, together with every coefficient and standard error in the associated Cloud demand, Cloud revenue, Cloud infrastructure-production, AI demand, AI revenue, and AI infrastructure-production equations. The table also reports the model's endogeneity treatment, fixed-effects structure, number of observations, and goodness of fit.

Table B-4. 3SLS estimates of the regional simultaneous-equation models

Variables	United States	Canada	Europe	Asia-Pacific	Latin America	MENA, South Africa and Türkiye
Dependent variable:	log(Y)	log(VA)	log(Y)	log(GDP)	log(GDP)	log(GDP)
Log(K)	0.396*** [0.024]	0.711*** [0.019]	0.283*** [0.034]	0.581*** [0.087]	0.476*** (0.091)	0.313*** [0.074]
Log(L)	0.642*** [0.016]	0.275*** [0.022]	0.659*** [0.057]	0.761*** [0.120]	0.206** (0.102)	0.278*** [0.095]
Log(CLOUD)	0.079* [0.046]	0.128** [0.057]	0.393** [0.190]	0.085*** [0.031]	0.323* (0.191)	0.122*** [0.044]
Log(CLOUD) × AI MODERATE	0.035*** [0.008]	—	—	-0.002 [0.004]	-0.001 (0.004)	—
Log(CLOUD) × AI ABOVE MEDIAN	—	—	0.031** [0.015]	—	—	—
Log(CLOUD) × AI INTENSIVE	0.068*** [0.009]	—	—	0.009* [0.005]	0.009*** (0.003)	—
Log(CLOUD) × AI	—	0.001* [0.001]	—	—	—	0.001*** [0.000]
AI	0.031*** [0.004]	—	0.002 [0.005]	—	0.052*** (0.020)	—
Log(Human capital)	—	—	—	—	—	-0.269*** [0.095]
Log(Oil price)	—	—	—	—	—	0.054*** [0.011]
Dependent variable:	log(Cloud)	log(Cloud)	log(Cloud)	log(Cloud)	log(Cloud)	log(Cloud)
Log(Cloud price / cost)	-0.031** [0.015]	0.085 [0.063]	-0.362*** [0.061]	-0.060*** [0.019]	-0.023** (0.011)	0.001 [0.006]
Log(Y/L)	-0.016 [0.022]	—	—	—	—	—
Log(Income)	—	0.020 [0.020]	—	—	—	—
Log(Y/Firm)	—	—	0.067 [0.052]	—	—	—

Variables	United States	Canada	Europe	Asia-Pacific	Latin America	MENA, South Africa and Türkiye
Log(GDP per capita)	—	—	—	2.894*** [0.548]	0.062 (0.090)	0.742*** [0.212]
Log(Software)	0.151*** [0.016]	—	—	—	—	—
Log(ERP)	—	-0.003 [0.024]	-0.022 [0.092]	—	—	—
Log(CRM)	—	0.138*** [0.032]	0.312*** [0.106]	—	—	—
Urban	0.038 [0.035]	—	0.659*** [0.221]	-0.009 [0.033]	0.095*** (0.012)	-0.018 [0.013]
Log(STEM)	0.001 [0.019]	—	—	—	—	—
Log(Human capital)	—	—	0.061 [0.089]	-0.375 [0.561]	0.010* (0.006)	0.176 [0.168]
ICT human capital	—	0.005*** [0.002]	—	—	—	—
Log(FTTH)	—	0.101* [0.060]	—	—	—	—
Firms not requiring ICT	—	-0.020*** [0.002]	—	—	—	—
Log(Broadband speed)	—	—	—	—	0.156*** (0.013)	—
Dependent variable:	log(Cloud rev.)	log(Cloud rev.)	log(Cloud rev.)	log(Cloud rev.)	log(Cloud rev.)	log(Cloud rev.)
Log(Cloud price / cost)	0.955*** [0.006]	0.113 [0.156]	0.903*** [0.037]	-0.032** [0.016]	-0.249*** (0.048)	0.043* [0.025]
Log(Y)	0.976*** [0.005]	—	0.963*** [0.042]	—	—	—
Log(GDP per capita)	—	—	—	3.837*** [0.612]	-0.475 (0.357)	—
Urban	—	—	—	0.266*** [0.035]	0.420*** (0.036)	0.0495*** [0.040]
Cloud producers	0.000 [0.000]	—	—	—	—	—
Cloud companies	—	—	0.180*** [0.032]	0.526*** [0.180]	0.418** (0.204)	0.255** [0.128]
Firms per Cloud company	—	0.005*** [0.000]	—	—	—	—
Availability zones	—	—	—	0.011** [0.005]	—	0.084*** [0.016]
Availability zones × Ontario	—	0.393*** [0.059]	—	—	—	—
Availability zones × British Columbia	—	0.290*** [0.078]	—	—	—	—
Dependent variable:	log(ΔCloud)	log(ΔCloud)	log(ΔCloud)	log(ΔCloud)	log(ΔCloud)	log(ΔCloud)
Log(Cloud revenue)	0.081*** [0.005]	0.698*** [0.258]	0.084*** [0.022]	0.055*** [0.015]	0.445*** (0.106)	0.396*** [0.023]
Dependent variable:	log(AI)	log(AI)	log(AI)	log(AI)	log(AI)	log(AI)
Log(AI price / ARPU)	-0.100*** [0.025]	-0.003*** [0.001]	-0.453*** [0.124]	-0.566*** [0.070]	-0.593*** (0.078)	-1.402*** [0.135]

Variables	United States	Canada	Europe	Asia-Pacific	Latin America	MENA, South Africa and Türkiye
Log(Y/L)	0.036** [0.015]	—	—	—	—	—
Log(Income)	—	0.093** [0.037]	—	—	—	—
Log(Y/Firm)	—	—	0.022 [0.112]	—	—	—
Log(GDP per capita)	—	—	—	5.027*** [0.940]	2.197*** (0.333)	0.702*** [0.108]
Log(Software)	0.006 [0.010]	—	—	—	—	—
Log(ERP)	—	0.039 [0.043]	0.344** [0.145]	—	—	—
Log(CRM)	—	0.197*** [0.056]	0.295* [0.158]	—	—	—
Urban	-0.008 [0.023]	—	0.332 [0.336]	0.408*** [0.050]	0.145*** (0.051)	0.031*** [0.006]
Log(STEM)	0.006 [0.010]	—	—	—	—	—
Log(Human capital)	—	—	-0.134 [0.133]	0.395 [0.424]	0.006 (0.009)	-0.486*** [0.154]
ICT human capital	—	0.008*** [0.003]	—	—	—	—
Log(FTTH)	—	0.142 [0.105]	—	—	—	—
Firms not requiring ICT	—	-0.010** [0.004]	—	—	—	—
Log(Broadband speed)	—	—	—	—	0.121*** (0.025)	—
Dependent variable:	log(AI rev.)	log(AI rev.)	log(AI rev.)	log(AI rev.)	log(AI rev.)	log(AI rev.)
Log(AI price / ARPU)	0.973*** [0.023]	-0.005*** [0.001]	0.813*** [0.095]	0.366*** [0.066]	0.150* (0.080)	0.722*** [0.065]
Log(Y)	1.076*** [0.006]	—	0.970*** [0.106]	—	—	—
Log(GDP per capita)	—	—	—	5.201*** [0.933]	2.156*** (0.341)	—
Urban	—	—	—	0.042*** [0.049]	0.122** (0.054)	0.078*** [0.025]
AI producers	0.001 [0.006]	—	—	—	—	—
AI companies	—	—	0.022 [0.029]	0.012** [0.005]	-0.003 (0.083)	-0.016*** [0.006]
Firms per AI company	—	0.031*** [0.003]	—	—	—	—
AI publications, U. Toronto × Ontario	—	0.126*** [0.031]	—	—	—	—
AI publications, UBC × British Columbia	—	0.067 [0.064]	—	—	—	—
AI venture capital × Ontario	—	0.424** [0.205]	—	—	—	—
AI venture capital × British Columbia	—	0.357 [0.324]	—	—	—	—
Dependent variable:	log(ΔAI)	log(ΔAI)	log(ΔAI)	log(ΔAI)	log(ΔAI)	log(ΔAI)

Variables	United States	Canada	Europe	Asia-Pacific	Latin America	MENA, South Africa and Türkiye
Log(AI revenue)	0.421*** [0.006]	0.418*** [0.097]	0.279*** [0.038]	0.135*** [0.024]	3.241*** (0.470)	1.538*** [0.047]
Model structure and fit						
Treatment of Cloud	—	Endog.	—	—	—	—
Treatment of AI	—	Endog.	—	—	—	—
State fixed effects (all equations)	YES	—	—	—	—	—
Country fixed effects	—	—	YES	YES	YES	YES
Sector fixed effects (output equation)	YES (interact.)	—	—	—	—	—
Sector fixed effects (remaining equations)	YES	—	—	—	—	—
Two-digit sector fixed effects	—	YES	—	—	—	—
Sector fixed effects	—	—	YES	—	—	—
Year fixed effects	—	YES	—	—	YES	—
Time trend(s)	—	—	—	YES	—	YES
Observations	878	249	178 (*)	110	77	98
R-squared (output equation)	0.974	0.97	0.982	0.99	0.99	0.99
Estimation method	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in brackets or parentheses; an em dash denotes a variable excluded from the selected specification.

(*) The 178 observations correspond to the 3SLS simultaneous-equation model, whereas the 185 observations correspond to the fixed-effects output and productivity regressions. The 3SLS model requires each country-sector observation to have complete information for all the equations and variables included in the system. This stricter complete-case requirement excludes seven observations that can still be used in the fixed-effects model.

Source: Telecom Advisory Services analysis

To estimate the Cloud spillover for Europe, we use the more conservative fixed-effects specification reported in Table B-5 rather than the larger elasticity obtained from the regional 3SLS model presented in Table B-4. The model is estimated on a cross-section of nine economic sectors in 26 European countries for 2021 and includes country and sector fixed effects, with robust standard errors clustered at the country level. The baseline output elasticity with respect to Cloud adoption is 0.135%. For observations with AI use above the sample median, the interaction term adds 0.043 percentage points, yielding the 0.178% elasticity applied in the European impact estimates.

Table B-5. Fixed effects estimates for Europe: output equation

Dep. var.: log(Y)	log(Y)
log(K)	0.285*** [0.053]
log(L)	0.647*** [0.077]
Log (CLOUD)	0.135* [0.079]
Log (CLOUD)#AI > MEDIAN	0.043*** [0.014]

AI	0.002 [0.005]
Country Fixed Effects	YES
Sector Fixed Effects	YES
Observations	185 (*)
R-squared	0.985

*Note: *** $p < 0.01$, * $p < 0.1$. Robust standard errors in brackets.*

(*) A fully populated dataset comprising 26 countries and nine sectors would contain 234 country-sector observations. The fixed-effects estimation uses 185 observations because one or more of the variables required by the regression are unavailable for some country-sector combinations.

Source: Telecom Advisory Services analysis

B.3.3. Conclusions

All six models find positive Cloud-output effects. We estimate the cloud spillover by region considering the coefficients of 0.079% (United States), 0.128% (Canada), 0.178% (Europe), 0.085% (Asia-Pacific), 0.323% (Latin America), and 0.122% (MENA). AI is measured separately in Chapter C.

C. ECONOMETRIC MODEL TO ESTIMATE AI ECONOMIC IMPACT

C.1. The theoretical model

The goal is to specify a common theoretical model for the six study regions that identifies the mechanisms through which AI spending can affect economic output. The model is estimated empirically using an international macroeconomic panel of 26 countries between 2019 and 2023 and is then applied consistently to the United States, Canada, Europe, Asia-Pacific, Latin America, and MENA, South Africa and Türkiye. To allow different elasticities of substitution between factors, we use a two-level CES (Constant Elasticity of Substitution) production function (Sato, 1967; Duffy et al., 2003). The factors of production are physical capital (K), skilled labor (S), and unskilled labor (N), whose basic specification is modeled as follows:

$$Y_{it} = A_{it} \left[\alpha [\beta A_{it}^K K_{it}^\theta + (1 - \beta) A_{it}^S S_{it}^\theta]^\frac{\rho}{\theta} + (1 - \alpha) N_{it}^\rho \right]^\frac{1}{\rho}$$

Where Y represents the gross domestic product (GDP), and the subscripts i and t indicate country and year, respectively. The term A_{it} represents total factor productivity. On the other hand, α and β are parameters that take values between zero and one, and that reflect the relative importance of the different factors of production. A key element of the proposed production function is the interpretation of the parameters θ and ρ , depending on the value they take, will allow us to evaluate to what extent the different factors of production are complementary or substitutive.

As the name implies, the CES production function exhibits constant elasticity of substitution between factors. This is a general framework that is conducive to estimating how the different factors of production are linked. In this sense, it is worth mentioning that the production functions of fixed proportions that denote perfect complementarity (Leontief), the linear function that denotes perfectly substitutive factors, and the Cobb-Douglas are all particular cases of the CES production function.

Starting with θ , this parameter will allow us to identify the relationship between skilled labor and physical capital. The elasticity of substitution between physical capital and skilled labor can be approximated as follows $\sigma_{K-S} = \frac{1}{1-\theta}$, so it can be stated that:

$$\sigma_{K-S} = \begin{cases} 0 & \text{if } \theta \rightarrow -\infty \\ 1 & \text{if } \theta = 0 \\ \infty & \text{if } \theta = 1 \end{cases}$$

From which it can be deduced that physical capital and skilled labor will be:

$$\left\{ \begin{array}{ll} \text{complementary perfect,} & \text{if } \theta \rightarrow -\infty \\ \text{complementary no perfect,} & \text{if } -\infty < \theta < 0 \\ \text{independent,} & \text{if } \theta = 0 \\ \text{substitutability no perfect,} & \text{if } 0 < \theta < 1 \\ \text{substitutability perfect,} & \text{if } \theta = 1 \end{array} \right.$$

Therefore, a positive value of θ would indicate a substitutability relationship, while a negative one would mean complementarity. On the other hand, if such a parameter were zero, both factors of production would be independent (as reflected, for example, in the Cobb-Douglas production functions). Considering the specialized literature (Duffy et al., 2003; Krusell et al., 2000), we expect the link between physical capital and skilled labor to be complementary ($\theta < 0$).

On the other hand, and following Duffy et al. (2003), we assume that physical capital and skilled labor act as a composite factor in their relationship with unskilled labor. In this way, the link between the two is interpreted from the parameter ρ . Therefore, the elasticity of substitution between the compound factor and unskilled labor is represented as $\sigma_{KS-N} = \frac{1}{1-\rho}$, so it can be stated that:

$$\sigma_{KS-N} = \begin{cases} 0 & \text{if } \rho \rightarrow -\infty \\ 1 & \text{if } \rho = 0 \\ \infty & \text{if } \rho = 1 \end{cases}$$

From which it can be deduced that the compound factor and unskilled labor will be:

$$\begin{cases} \text{complementary perfect} & , & \text{if } \rho \rightarrow -\infty \\ \text{complementary no perfect,} & & \text{if } -\infty < \rho < 0 \\ \text{independents,} & & \text{if } \rho = 0 \\ \text{substitutability no perfect,} & & \text{if } 0 < \rho < 1 \\ \text{substitutability perfect} & , & \text{if } \rho = 1 \end{cases}$$

Thus, ρ will take a positive value in the case of substitutability and a negative value in the case of complementarity (and zero in the case of the composite factor and the unskilled work being independent of each other). Naturally, in this case we expect capital and skilled labor to act as substitutes for unskilled labor ($\rho > 0$).

A relevant aspect in the analysis will depend on the treatment to be given to A_{it}^K and A_{it}^S , that is, the productivity associated with capital and skilled labor, respectively. Given that the objective of this work is to analyze the role of AI in this matter, we model both elements as follows:

$$\begin{aligned} A_{it}^K &= e^{\delta_K AI_{it}} \\ A_{it}^S &= e^{\delta_S AI_{it}} \end{aligned}$$

In other words, the objective is to verify to what extent spending on AI contributes to increasing the productivity of capital and skilled labor. In this sense, if it is verified that $\delta_K > 0$, this would imply that AI increases the marginal productivity of capital, while a hypothetical value of $\delta_S > 0$ would imply that AI increases the marginal productivity of skilled labor. Similarly, if $\delta_K = 0$ or $\delta_S = 0$, this would imply that AI plays no role in increasing the marginal productivity of capital or skilled labor, respectively.

Substituting the terms associated with the productivity of capital and skilled labor in the production function, we obtain:

$$Y_{it} = A_{it} \left[\alpha [\beta (e^{\delta_{KAI_{it}}} K_{it})^\theta + (1 - \beta) (e^{\delta_{SAI_{it}}} S_{it})^\theta]^\frac{\rho}{\theta} + (1 - \alpha) N_{it}^\rho \right]^\frac{1}{\rho}$$

Applying logarithms to the production function, the following expression is obtained:

$$\ln Y_{it} = \ln A_{it} + \frac{1}{\rho} \ln \left[\alpha [\beta (e^{\delta_{KAI_{it}}} K_{it})^\theta + (1 - \beta) (e^{\delta_{SAI_{it}}} S_{it})^\theta]^\frac{\rho}{\theta} + (1 - \alpha) N_{it}^\rho \right]$$

Where it is appreciated that important nonlinearities persist, coming from the nature of the CES function. This implies that the econometric analysis cannot be performed through ordinary least squares (OLS), but through nonlinear least squares (NLS).

C.2. Empirical estimation of the model

A panel of 26 countries was constructed for 2019–2023, covering the recent period of rapid AI expansion and including observations from all six study regions. The pooled international sample is required because consistent country-level time series for the complete production function are not available separately for every region. The countries included are shown in Table C-1.

Table C-1. Countries included in the sample

Argentina	France	Korea	Spain
Australia	Germany	Mexico	Türkiye
Brazil	Hong Kong	Peru	United Arab Emirates
Canada	India	Russia	United Kingdom
Chile	Israel	Saudi Arabia	United States
China	Italy	Singapore	
Colombia	Japan	South Africa	

Source: Telecom Advisory Services

The variables to be used in the empirical estimation of the model are detailed in Table C-2. The dependent variable will be the gross domestic product (GDP), obtained from the International Monetary Fund (IMF) database. For the capital stock, the 2019 value reported in the Penn World Tables (PWT) is taken, and it is projected until 2023 to take the annual investment according to the IMF and the capital depreciation rate per country according to PWT. Both GDP and capital stock are deflated and converted to purchasing power parity (PPP), in 2021 dollars.

Table C-2. Variables to be used in econometric regressions

Variable	Description	Mean	Standard Deviation	Source
Y	Real Gross Domestic Product (2021 USD billions, PPP)	4,465.637	6,724.309	IMF
K	Real physical capital stock (2021 trillions of dollars in PPPs).	18,864.270	27,425.060	PWT/IMF

S	Skilled labor (workers with tertiary education, in the thousands)	19,711.680	30,540.920	IMF / WB
N	Unskilled work (workers without tertiary education, in the thousands)	59,807.830	138,788.300	IMF / WB
AI	AI spending (USD billions)	4.938	12.756	IDC
ChatGPT visits	Number of visits to the ChatGPT domain (in millions)	125.714	458.417	Semrush
ChatGPT users	Number of unique users who have visited the ChatGPT domain (in millions)	28.345	106.736	Semrush
BB	Fixed broadband penetration (% households)	1.005	0.657	ITU/TAS

Source: Telecom Advisory Services

The level of employment is obtained from the IMF, and the number of workers will be classified as skilled or unskilled depending on the attainment of a tertiary degree. To do this, the percentage of the population over 25 years of age with tertiary education according to the World Bank is taken as a reference, which is multiplied by the number of workers to make the distinction between skilled and unskilled.

With respect to AI, the variable of expenditure on this technology, reported by IDC, is taken as a reference. A relevant aspect to consider is whether this variable should also be deflated and converted to PPP as was done with GDP and capital. For consistency with the other variables, the conversion should be carried out, although this generates a series of drawbacks. First, because the GDP deflator is not a valid index to remove inflation from AI spending, since it is an indicator that considers all the products produced in the country, while in this case it is a single and concrete element, such as AI spending. This argument is reinforced when one takes into account that, unlike the rest of the economy, digital goods and services tend to have decreasing prices (as projected by Moore's Law), i.e. they do not usually respond to inflationary adjustment parameters, which makes it advisable not to make such an adjustment in the absence of a sector-specific price index. In addition, the conversion to PPP becomes meaningless assuming that prices are relatively uniform across countries, with a limited number of suppliers supplying the entire world. Considering all this, in econometric regressions the AI variable will be used in both its adjusted and unadjusted versions, and the results will be discussed.

Finally, all estimates incorporate fixed effects by country and by year. This allows us to absorb unobservable aspects that can make some countries more productive than others for cultural, idiosyncratic, or institutional reasons, as long as they are invariant over time. The addition of fixed effects per year, on the other hand, allows us to contemplate exogenous technological growth, as well as absorb cyclical shocks that affect all economies as a whole (for example, the effects of COVID-19 in 2020). In this way, the term A_{it} represented in the production function is treated.

C.3. Results for the base model

In columns (i) and (ii) we present the regressions that represent the base model, with the AI variable adjusted by PPP at constant prices and without making such adjustment, as

discussed above. In both cases, δK is not statistically significant, suggesting that AI spending has not contributed to making physical capital more productive. In contrast, δS is positive and statistically significant, with coefficients ranging from 0.38 to 0.62, suggesting that AI has contributed to increasing the productivity of skilled labor. The model when the AI variable is included without deflating or adjusting for PPP seems to work better, reflecting a better fit according to the adjusted R squared and by the sum of squares of the residuals. This will be verified in the remaining pairs of estimates reported in Table C-3 ((iii) vs (iv); (v) vs (vi); and (vii) vs (viii)). For this reason, it is considered convenient to proceed with the analysis using the unadjusted version of this variable.

Table C-3. Nonlinear Least Squares Estimates

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Constant	-1.7400*** [0.1606]	-1.3464*** [0.0247]	-1.4417*** [0.0731]	-1.5191*** [0.0568]	-1.4235*** [0.0182]	-1.6321*** [0.1049]	-1.8544*** [0.1718]	-1.4618*** [0.0558]
α	0.5575*** [0.0414]	0.5981*** [0.0311]	0.5381*** [0.0442]	0.5937*** [0.0314]	0.5566*** [0.0390]	0.5981*** [0.0313]	0.5383*** [0.0406]	0.5938*** [0.0316]
β	0.1563* [0.0861]	0.2151*** [0.0648]	0.1387 [0.0865]	0.2121*** [0.0655]	0.1594** [0.0740]	0.2117*** [0.0607]	0.1381* [0.0752]	0.2080*** [0.0613]
ρ	0.9348*** [0.2569]	0.9310*** [0.2505]	0.8847*** [0.2606]	0.9103*** [0.2616]	0.9310*** [0.2538]	0.9308*** [0.2489]	0.8857*** [0.2588]	0.9120*** [0.2607]
θ	-1.7217 [1.4648]	-1.0616 [0.6492]	-1.6121 [1.5684]	-1.0496 [0.6524]	-1.6106*** [0.4304]	-1.2078*** [0.2094]	-1.6376*** [0.4484]	-1.2101*** [0.2120]
Δk	0.0100 [0.1042]	-0.0248 [0.1072]	-0.0026 [0.1418]	-0.0275 [0.1112]				
δs	0.3848** [0.1685]	0.6180*** [0.0774]	0.4367** [0.2051]	0.6228*** [0.0782]	0.3911*** [0.1341]	0.6201*** [0.0826]	0.4348*** [0.1454]	0.6250*** [0.0836]
δBB			-0.0311 [0.0397]	-0.0120 [0.0369]			-0.0310 [0.0389]	-0.0113 [0.0369]
Country fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Fixed year effects	YES	YES	YES	YES	YES	YES	YES	YES
AI Variable	Adjusted for constant prices and PPAs	Not adjusted	Adjusted for constant prices and PPAs	Not adjusted	Adjusted for constant prices and PPAs	Not adjusted	Adjusted for constant prices and PPAs	Not adjusted
Resid. SS	0.0688	0.0629	0.0683	0.0627	0.0688	0.0629	0.0683	0.0628
Adj R2	0.9994	0.9995	0.9994	0.9995	0.9994	0.9995	0.9994	0.9995
Obs	130	130	129	129	130	130	129	129 (*)
Method	NLS	NLS	NLS	NLS	NLS	NLS	NLS	NLS

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors are reported in brackets.

(*) The balanced international panel contains 130 country-year observations: 26 countries over five years. Specifications (iii), (iv), (vii), and (viii) additionally include the fixed-broadband penetration control. The four models that included the broadband effect, lost one observation because of no data for one period for that variable

Source: Telecom Advisory Services

Other results to highlight in the model is that $\rho > 0$, which suggests substitution between the composite factor (capital and skilled labor, also influenced by AI) and unskilled labor. It is worth mentioning that the values ρ it takes are close to unity, which indicates a high degree of substitution. On the other hand, the role of AI in capital productivity is verified $\theta < 0$, although it is only statistically significant once the role of AI in capital productivity is omitted from the regressions (since it is not significant in any case, it is omitted in the regressions that go from column (v) to (viii)). This suggests evidence of complementarity between physical capital and skilled labor, as expected according to what has been reported in the literature.

On the other hand, in certain regressions we incorporate fixed broadband penetration as part of the component A_{it} , i.e. as an element of factor-neutral productivity. The aim is to be able to control by the diffusion of less sophisticated digital technologies (columns (iii), (iv), (vii) and (viii)). The results for the parameters associated with AI do not change, and it can therefore be said that the role of this technology to increase the productivity of skilled labor is robust.

C.4. Controlling endogeneity

In this section we address the possible endogeneity problems that may arise associated with the AI variable. It is possible that the economic activity variable and the AI variable are determined simultaneously. On the other hand, both variables could be influenced by other variables not included in the model, although the latter risk is lower given that the regressions carried out incorporate fixed effects of country and year, and relevant variables such as skilled work and broadband penetration. To this end, the Generalized Method of Moments (GMM) methodology will be used, which allows the incorporation of instruments and at the same time the estimation of non-linear models. As instruments, we use the number of academic papers on AI-related topics published by local universities in the past (we take the periods 2005-2009, 2010-2014, and 2015-2019). The results are presented in Table C-4.

Table C-4. Generalized Method of Moments Estimates

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Constant	-1.5736*** [0.0370]	-1.5727*** [0.0886]	-1.5733*** [0.0896]	-1.5473*** [0.0295]	-1.6006*** [0.3748]	-1.5803*** [0.4599]
α	0.5786*** [0.0888]	0.5606*** [0.1140]	0.5456*** [0.1158]	0.5502*** [0.0547]	0.6023*** [0.1375]	0.6082*** [0.1660]
β	0.2965** [0.1305]	0.2457** [0.1122]	0.2704*** [0.0934]	0.2485*** [0.0683]	0.2721*** [0.0736]	0.2909*** [0.0766]
ρ	0.7254 [0.7541]	0.6249 [1.0775]	0.4560 [1.0886]	0.5152 [0.5131]	0.9689 [1.3039]	0.9873 [1.5821]
θ	-0.7820 [2.5082]	-1.2073 [2.3189]	-0.7950 [1.7491]	-1.0829*** [0.1940]	-0.9876*** [0.1774]	-0.9622*** [0.1655]
Δk	-0.0285 [0.6313]	0.0206 [0.2916]	-0.0454 [0.4355]			
δs	0.6960*** [0.2591]	0.5852*** [0.2032]	0.6032** [0.2937]	0.5567*** [0.1240]	0.6595*** [0.1776]	0.6699*** [0.2265]
δBB		0.0080	-0.0206		0.0252	0.0072

		[0.0666]	[0.0735]		[0.0724]	[0.0771]
Country fixed effects	YES	YES	YES	YES	YES	YES
Fixed year effects	YES	YES	YES	YES	YES	YES
AI treatment	Endogenous	Endogenous	Endogenous	Endogenous	Endogenous	Endogenous
BB Treatment	n.a.	Exogenous	Endogenous	n.a.	Exogenous	Endogenous
Observations	125	124	124	125	124	124
Method	GMM	GMM	GMM	GMM	GMM	GMM

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors are reported in brackets.

Source: Telecom Advisory Services

The estimates presented in column (i) verify the previous results, in the sense that the parameter δ_s is positive and significant, again verifying the relevance of AI to increase the productivity of skilled labor. Likewise, in the regressions presented in columns (ii) and (iii) we introduce broadband penetration as part of TFP, without significantly altering the results regarding the role of AI. This is done by considering broadband first as exogenous (in column (ii)) and then as endogenous (column (iii)), using as instruments the penetration of fixed telephony with a delay of 5 years.

The results are robust in verifying that AI has indeed contributed to increasing the productivity of skilled labor, although there is no evidence that it has done the same, for the moment, with the productivity of capital. This could be explained by the fact that AI is more likely to be applied to increase labor productivity (of skilled labor) than the efficiency with which firms use their fixed assets (such as machinery, buildings, and equipment). generating potential negative effects on the workforce.

C.5. Elasticity calculation derived from the econometric model

Taking the estimated production function, in logarithms, and deriving with respect to AI, this derives in the following expression:

$$\frac{\partial \ln Y_{it}}{\partial AI} = \left[\frac{\alpha [\beta (K_{it})^\theta + (1 - \beta) (e^{\delta_s AI_{it}} S_{it})^\theta]^{\frac{\rho - \theta}{\theta}} (1 - \beta) e^{\theta \delta_s AI_{it}} (S_{it})^\theta \delta_s}{\alpha [\beta (K_{it})^\theta + (1 - \beta) (e^{\delta_s AI_{it}} S_{it})^\theta]^{\frac{\rho}{\theta}} + (1 - \alpha) N_{it}^\rho} \right]$$

Substituting the parameters estimated in the most conservative regression for the impact of AI, among those that omit the non-significant effect of the effect of AI on capital productivity (that presented in column (v) of Table C-3), and substituting the values of the variables for the means of the sample, the result of this derivative can be obtained:

$$\frac{\partial \ln Y_{it}}{\partial AI} = 0.0999$$

However, to analyze such a result, it is important to consider that the AI variable has been standardized to carry out econometric regression. Therefore, the increase of one unit in such a variable (which is measured through the derivative reported above) is equivalent to the increase of a standard deviation, which, in its non-standardized version, represents 12,756

billion dollars as observed in Table C-2. This represents an increase of 158.3% of the average value (4,936 billion), or 1153.6% if we take the median as a reference. Therefore, if a variation representing an increase of 158.3% from the mean value (or 1153.6% with respect to the median) is associated with a value of 0.0999 in the reported derivative, it can be inferred that a variation representing 1% of the increase in AI spending will represent an increase in GDP of between 0.01% and 0.06%, depending on the criterion taken as a reference (mean or median). Taking the average of both values, we can link 1% of the growth in AI spending to 0.036% of GDP growth. We will use as a starting point the most conservative value: 0.01%, and after the first year, we will be more optimistic until reaching the mean value between both coefficients: 0.036% (See Table C-5).

Table C-5. Coefficients of Impact of 1% growth in AI spending on GDP growth (2025-2030)

	2025	2026	2027	2028	2029	2030
Coefficient	0.010%	0.013%	0.017%	0.022%	0.028%	0.036%

Source: Telecom Advisory Services

D. REVENUE DATA SOURCES AND COUNTRY-LEVEL IDC COVERAGE

D.1. Database and common treatment

The 2025–2030 impact estimates use a common set of revenue and macroeconomic inputs. Table D-1 identifies the database release used for each input and distinguishes the observed forecast horizon from the model extensions. All revenue values are expressed in current US dollars and aggregated in USD millions. GDP is expressed in current US dollars because the spillover calculation measures the contribution to nominal economic output.

Table D-1. Databases used in the 2025–2030 estimates

Input	Source database	Release / extraction	Observed horizon used	Treatment in the model
Gross Cloud revenue	<i>IDC Semiannual Public Cloud Services Tracker-2024H2 Forecast</i>	July 2024	2025–2028	Used before deducting Cloud-enabled AI spending; 2029–2030 projected
Cloud-enabled AI spending	<i>IDC Semiannual Public Cloud Services Tracker-2024H2 Forecast</i>	July 2024	2025–2028	Deducted from gross Cloud revenue; 2029–2030 projected
AI spending	<i>IDC Worldwide AI and Generative AI Spending Guide – April 2026</i>	April 2026	2025–2029	Used as the AI direct contribution; 2030 projected
GDP	International Monetary Fund database	27 July 2026 extraction	2025–2030	Converted from USD billions to USD millions; regional growth used only for isolated country gaps

Source: IDC and International Monetary Fund databases; Telecom Advisory Services methodology.

D.2. Country allocation and forecast rules

IDC direct country series are used without cross-country allocation. When IDC reports only a residual regional aggregate (“Rest of ...”), the model preserves that IDC aggregate as the control total and produces country estimates. Gross Cloud revenue and Cloud-enabled AI spending are allocated in each year according to each uncovered country's share of GDP within the relevant residual geography:

$$\text{Value}_{c,t} = \frac{\text{GDP}_{c,t}}{\sum_{j \in R} \text{GDP}_{j,t}} \times \text{IDC}_t^{\text{Rest-of}}$$

For AI spending, the residual aggregate is allocated through 2024 according to each country's share of Cloud spending within the corresponding residual geography. From 2025 through 2029, each allocated country series follows the annual growth rate of the relevant IDC Rest-of AI aggregate. This approach uses Cloud market size as the observable country distribution key while preserving the IDC AI residual total.

$$AI_{c,t} = \frac{Cloud_{c,t}}{\sum_{j \in R} Cloud_{j,t}} \times IDC_t^{\text{Rest-of AI}}$$

For 2029–2030 Cloud revenue and Cloud-enabled AI spending, and for 2030 AI spending, the annual growth rate is extended by preserving the most recent proportional change in the growth rate:

$$g_t = g_{t-1} \times \frac{g_{t-1}}{g_{t-2}}$$

$$Value_t = Value_{t-1} \times (1 + g_t)$$

This rule continues the acceleration or deceleration already present in the IDC forecast rather than imposing a new external growth assumption.

Net Cloud revenue equals gross Cloud revenue less Cloud-enabled AI spending to avoid double counting with the AI spending. The Cloud spillover is calculated from the growth of net Cloud revenue, while the AI spending series and AI spillover are reported separately. The source classifications in Table D-2 apply to the observed IDC horizon; model-projected years inherit the same source lineage.

Table D-2. Country-level source lineage for Cloud revenue and AI spending

Country / economy	Cloud revenue basis	AI spending basis
United States		
United States	IDC direct country series	IDC direct country series
Canada		
Canada	IDC direct country series	IDC direct country series
Europe		
Austria	IDC Rest of Western Europe	IDC Rest of Western Europe
Belgium	IDC Rest of Western Europe	IDC Rest of Western Europe
Bulgaria	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Croatia	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Czechia	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Denmark	IDC Rest of Western Europe	IDC Rest of Western Europe
Estonia	TAS market proxy	TAS market proxy
Finland	IDC Rest of Western Europe	IDC Rest of Western Europe
France	IDC direct country series	IDC direct country series
Germany	IDC direct country series	IDC direct country series
Greece	IDC Rest of Western Europe	IDC Rest of Western Europe
Hungary	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Ireland	IDC Rest of Western Europe	IDC Rest of Western Europe
Italy	IDC direct country series	IDC direct country series

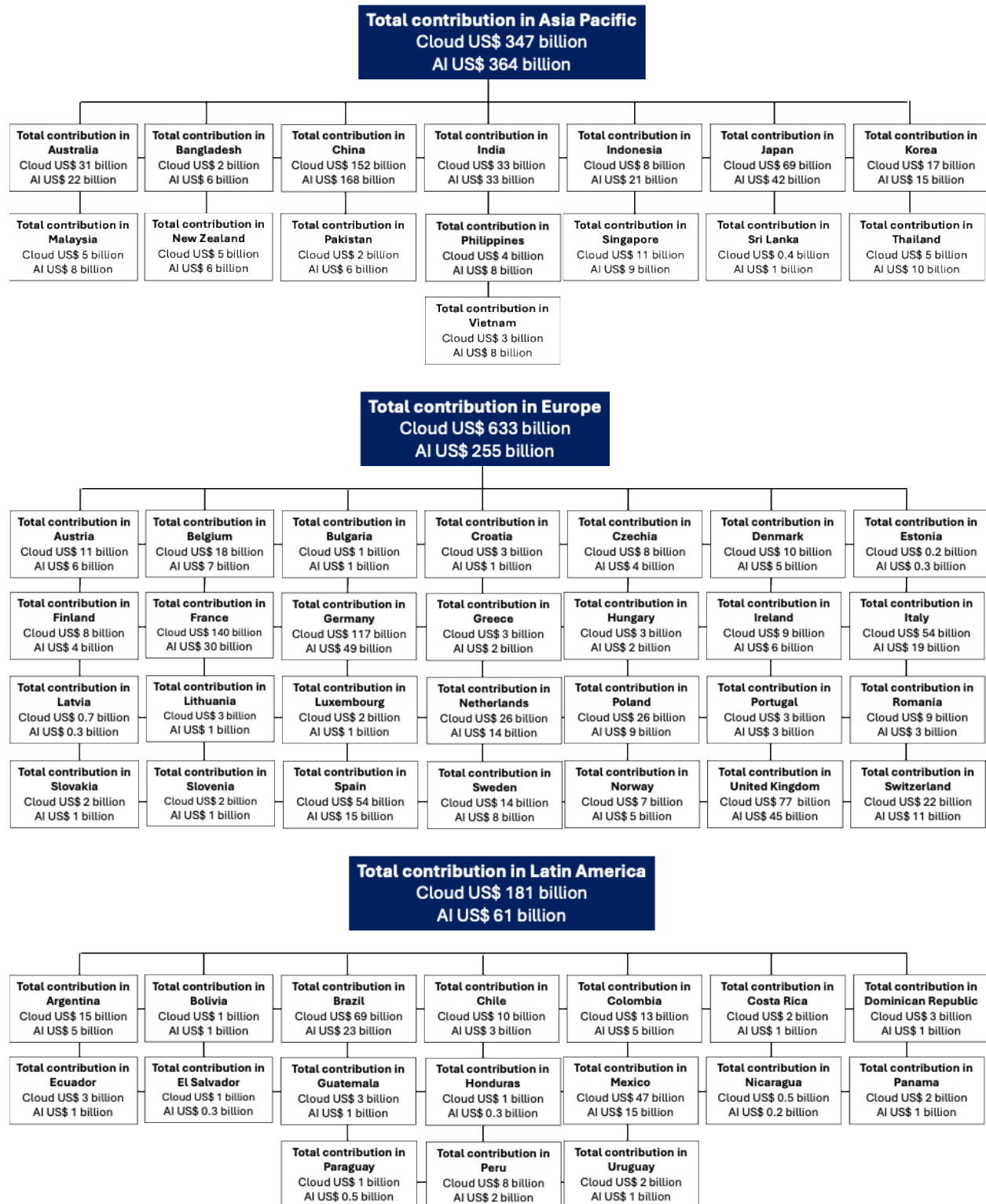
Country / economy	Cloud revenue basis	AI spending basis
Latvia	TAS market proxy	TAS market proxy
Lithuania	TAS market proxy	TAS market proxy
Luxembourg	TAS market proxy	TAS market proxy
Netherlands	IDC Rest of Western Europe	IDC Rest of Western Europe
Poland	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Portugal	IDC Rest of Western Europe	IDC Rest of Western Europe
Romania	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Slovakia	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Slovenia	IDC Rest of Central and Eastern Europe	IDC Rest of Central and Eastern Europe
Spain	IDC direct country series	IDC direct country series
Sweden	IDC Rest of Western Europe	IDC Rest of Western Europe
Norway	IDC Rest of Western Europe	IDC Rest of Western Europe
United Kingdom	IDC direct country series	IDC direct country series
Switzerland	IDC Rest of Western Europe	IDC Rest of Western Europe
Asia-Pacific		
Australia	IDC direct country series	IDC direct country series
Bangladesh	IDC Rest of Asia/Pacific	IDC Rest of Asia/Pacific
China	IDC direct country series	IDC direct country series
India	IDC direct country series	IDC direct country series
Indonesia	IDC direct country series	IDC Rest of Asia/Pacific
Japan	IDC direct country series	IDC direct country series
Korea	IDC direct country series	IDC direct country series
Malaysia	IDC direct country series	IDC Rest of Asia/Pacific
New Zealand	IDC direct country series	IDC Rest of Asia/Pacific
Pakistan	IDC Rest of Asia/Pacific	IDC Rest of Asia/Pacific
Philippines	IDC direct country series	IDC Rest of Asia/Pacific
Singapore	IDC direct country series	IDC direct country series
Sri Lanka	IDC Rest of Asia/Pacific	IDC Rest of Asia/Pacific
Thailand	IDC direct country series	IDC Rest of Asia/Pacific
Vietnam	IDC direct country series	IDC Rest of Asia/Pacific
Latin America		
Argentina	IDC direct country series	IDC direct country series
Bolivia	IDC Rest of Latin America	IDC Rest of Latin America
Brazil	IDC direct country series	IDC direct country series
Chile	IDC direct country series	IDC direct country series
Colombia	IDC direct country series	IDC direct country series
Costa Rica	IDC Rest of Latin America	IDC Rest of Latin America
Dominican Republic	IDC Rest of Latin America	IDC Rest of Latin America
Ecuador	IDC Rest of Latin America	IDC Rest of Latin America
El Salvador	IDC Rest of Latin America	IDC Rest of Latin America
Guatemala	IDC Rest of Latin America	IDC Rest of Latin America
Honduras	IDC Rest of Latin America	IDC Rest of Latin America
Mexico	IDC direct country series	IDC direct country series
Nicaragua	IDC Rest of Latin America	IDC Rest of Latin America
Panama	IDC Rest of Latin America	IDC Rest of Latin America
Paraguay	IDC Rest of Latin America	IDC Rest of Latin America
Peru	IDC direct country series	IDC direct country series
Uruguay	IDC Rest of Latin America	IDC Rest of Latin America

Country / economy	Cloud revenue basis	AI spending basis
MENA, South Africa and Türkiye		
Israel	IDC direct country series	IDC direct country series
Türkiye	IDC direct country series	IDC direct country series
South Africa	IDC direct country series	IDC direct country series
Algeria	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Bahrain	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Egypt	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Jordan	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Kuwait	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Morocco	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Oman	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Qatar	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
Saudi Arabia	IDC direct country series	IDC direct country series
Tunisia	IDC Rest of Middle East and Africa	IDC Rest of Middle East and Africa
United Arab Emirates	IDC direct country series	IDC direct country series

NOTE: "TAS market proxy" identifies countries for which Statista-based estimates were used to maintain consistency with previous reports.

Source: IDC Worldwide AI and Generative AI Spending Guide – April 2026; IDC Semiannual Public Cloud Services Tracker- 2024H2 Forecast; STATISTA; Telecom Advisory Services analysis

APPENDIX E. DETAILED ECONOMIC IMPACT BY COUNTRY (2025)



Total contribution in MENA, S. Africa & Turkey
Cloud US\$ 79 billion
AI US\$ 49 billion

Total contribution in Algeria Cloud US\$ 3 billion AI US\$ 2 billion	Total contribution in Bahrain Cloud US\$ 0.3 billion AI US\$ 0.3 billion	Total contribution in Egypt Cloud US\$ 4 billion AI US\$ 2 billion	Total contribution in Israel Cloud US\$ 16 billion AI US\$ 7 billion	Total contribution in Jordan Cloud US\$ 0.6 billion AI US\$ 0.5 billion	Total contribution in Kuwait Cloud US\$ 2 billion AI US\$ 1 billion	Total contribution in Morocco Cloud US\$ 2 billion AI US\$ 1 billion
Total contribution in Oman Cloud US\$ 1 billion AI US\$ 1 billion	Total contribution in Qatar Cloud US\$ 2 billion AI US\$ 1 billion	Total contribution in Saudi Arabia Cloud US\$ 12 billion AI US\$ 11 billion	Total contribution in South Africa Cloud US\$ 9 billion AI US\$ 4 billion	Total contribution in Turkey Cloud US\$ 16 billion AI US\$ 12 billion	Total contribution in Tunisia Cloud US\$ 11 billion AI US\$ 0.5 billion	Total contribution in United Arab Emirates Cloud US\$ 11 billion AI US\$ 6 billion

Total contribution in United States
Cloud US\$ 787 billion AI US\$ 754 billion

Total contribution in Alabama Cloud US\$ 8 billion AI US\$ 7 billion	Total contribution in Alaska Cloud US\$ 3 billion AI US\$ 2 billion	Total contribution in Arizona Cloud US\$ 14 billion AI US\$ 14 billion	Total contribution in Arkansas Cloud US\$ 4 billion AI US\$ 4 billion	Total contribution in California Cloud US\$ 117 billion AI US\$ 119 billion	Total contribution in Colorado Cloud US\$ 14 billion AI US\$ 14 billion	Total contribution in Connecticut Cloud US\$ 11 billion AI US\$ 10 billion
Total contribution in Delaware Cloud US\$ 3 billion AI US\$ 3 billion	Total contribution in D. of Columbia Cloud US\$ 5 billion AI US\$ 4 billion	Total contribution in Florida Cloud US\$ 40 billion AI US\$ 41 billion	Total contribution in Georgia Cloud US\$ 23 billion AI US\$ 23 billion	Total contribution in Hawaii Cloud US\$ 2 billion AI US\$ 2 billion	Total contribution in Idaho Cloud US\$ 3 billion AI US\$ 3 billion	Total contribution in Illinois Cloud US\$ 31 billion AI US\$ 29 billion
Total contribution in Indiana Cloud US\$ 14 billion AI US\$ 12 billion	Total contribution in Iowa Cloud US\$ 8 billion AI US\$ 7 billion	Total contribution in Kansas Cloud US\$ 6 billion AI US\$ 5 billion	Total contribution in Kentucky Cloud US\$ 7 billion AI US\$ 7 billion	Total contribution in Louisiana Cloud US\$ 8 billion AI US\$ 7 billion	Total contribution in Maine Cloud US\$ 2 billion AI US\$ 2 billion	Total contribution in Maryland Cloud US\$ 11 billion AI US\$ 11 billion
Total contribution in Massachusetts Cloud US\$ 22 billion AI US\$ 21 billion	Total contribution in Michigan Cloud US\$ 17 billion AI US\$ 16 billion	Total contribution in Minnesota Cloud US\$ 13 billion AI US\$ 12 billion	Total contribution in Mississippi Cloud US\$ 4 billion AI US\$ 3 billion	Total contribution in Missouri Cloud US\$ 11 billion AI US\$ 11 billion	Total contribution in Montana Cloud US\$ 2 billion AI US\$ 2 billion	Total contribution in Nebraska Cloud US\$ 5 billion AI US\$ 5 billion
Total contribution in Nevada Cloud US\$ 6 billion AI US\$ 6 billion	Total contribution in New Hampshire Cloud US\$ 3 billion AI US\$ 3 billion	Total contribution in New Jersey Cloud US\$ 21 billion AI US\$ 21 billion	Total contribution in New Mexico Cloud US\$ 3 billion AI US\$ 3 billion	Total contribution in New York Cloud US\$ 83 billion AI US\$ 74 billion	Total contribution in North Carolina Cloud US\$ 23 billion AI US\$ 22 billion	Total contribution in North Dakota Cloud US\$ 2 billion AI US\$ 2 billion
Total contribution in Ohio Cloud US\$ 25 billion AI US\$ 23 billion	Total contribution in Oklahoma Cloud US\$ 6 billion AI US\$ 6 billion	Total contribution in Oregon Cloud US\$ 8 billion AI US\$ 8 billion	Total contribution in Pennsylvania Cloud US\$ 28 billion AI US\$ 26 billion	Total contribution in Rhode Island Cloud US\$ 2 billion AI US\$ 2 billion	Total contribution in South Carolina Cloud US\$ 8 billion AI US\$ 8 billion	Total contribution in South Dakota Cloud US\$ 2 billion AI US\$ 2 billion
Total contribution in Tennessee Cloud US\$ 14 billion AI US\$ 14 billion	Total contribution in Texas Cloud US\$ 74 billion AI US\$ 71 billion	Total contribution in Utah Cloud US\$ 8 billion AI US\$ 8 billion	Total contribution in Vermont Cloud US\$ 1 billion AI US\$ 1 billion	Total contribution in Virginia Cloud US\$ 17 billion AI US\$ 17 billion	Total contribution in Washington Cloud US\$ 27 billion AI US\$ 28 billion	Total contribution in West Virginia Cloud US\$ 3 billion AI US\$ 2 billion
Total contribution in Wisconsin Cloud US\$ 12 billion AI US\$ 11 billion		Total contribution in Wyoming Cloud US\$ 1 billion AI US\$ 1 billion				

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