Telecom Advisory Services

# ECONOMIC IMPACT OF CLOUD COMPUTING IN THE UNITED KINGDOM

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# 1. INTRODUCTION

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. Among the most recent technological innovations, cloud computing is a powerful tool for organizations looking to execute significant production model changes, accomplish their strategic goals, and remain competitive. In light of this, cloud computing has become a key lever of national competitiveness and economic growth.

In this context, the purpose of this study is to analyze the contribution of cloud computing to the United Kingdom's economy. Research on **the macro-economic contribution of cloud computing has concluded that, driven by its impact on capital efficiency and stimulus of product development, it represents an engine of economic growth.** 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,[1] while the spillover effects are the benefits generated by cloud computing in terms of IT cost efficiencies, productivity, new product development, support for incubation of startups and the like.[2]

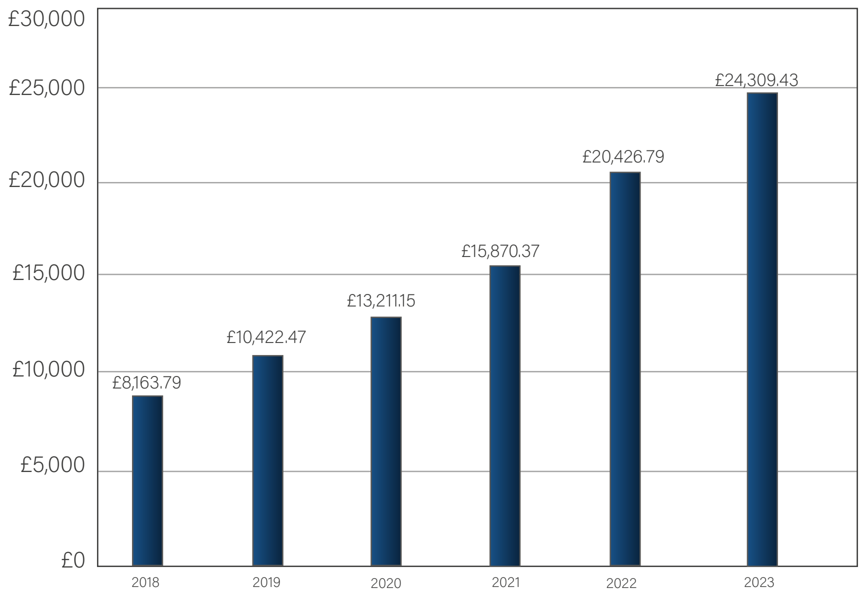
The study is structured as follows. In chapter 2, we present a brief description of the current state of adoption of cloud computing in the United Kingdom. Following this, chapter 3 introduces the theoretical model of an aggregate production function to estimate the economic growth of cloud computing. In chapter 4, we present the estimates of economic contribution in the aggregate for the whole country and disaggregated by industry. In chapter 5, we conclude with the principal findings. Appendix A presents the regression analysis used to link cloud spending and adoption, while Appendix B presents the dataset and the econometric models.

[1] *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.*
[2] *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.*

# 2. THE STATE OF DEVELOPMENT OF CLOUD COMPUTING IN THE UNITED KINGDOM

Cloud computing spending in the United Kingdom is the largest of Europe, accounting for £ 24.3 billion pounds in 2023 and representing the 23% of the total spending of the continent.[3] (see graphic 2-1).

**Graphic 2-1. United Kingdom: Cloud computing constant vendor revenues (in £ million) (2018-2023)**




*Note: AI Platforms excluded from cloud service provider revenues*
*Source: IDC Semiannual Public Cloud Services Tracker (2023H1 Release)*

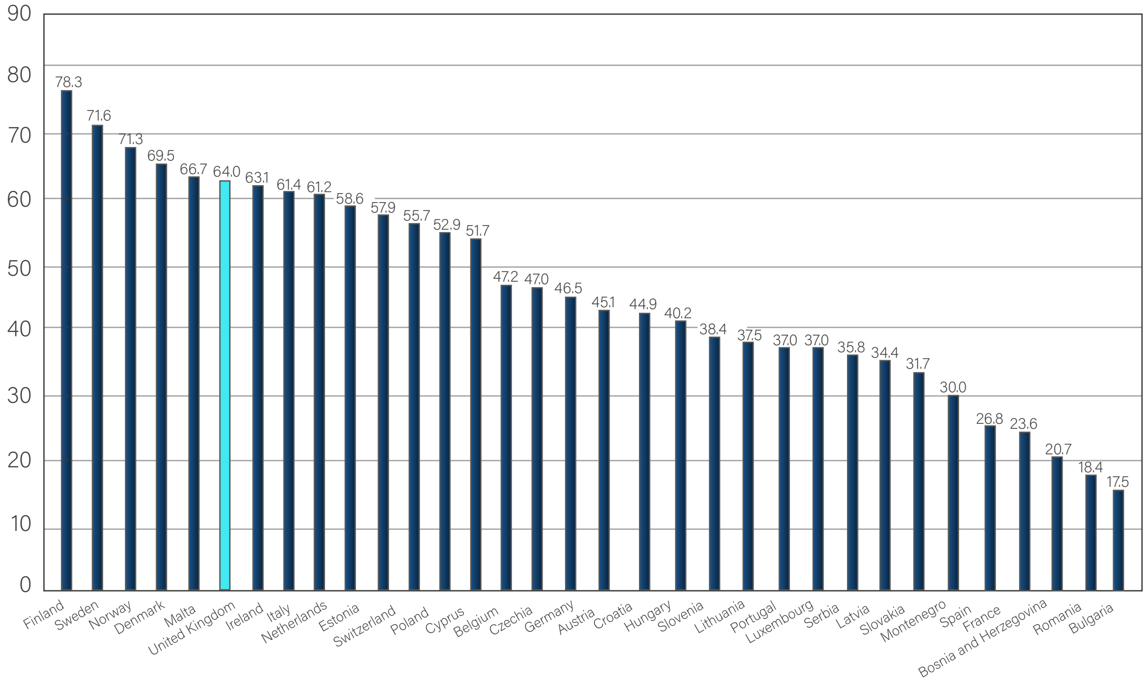
Since 2018, the cloud computing market in the United Kingdom has been growing at 24.9% CAGR, a similar growth rate than the world demand. At current levels, cloud spending represents 1.03% of 2023 British GDP.

Latest cloud penetration figures published for the United Kingdom point to 53% of firms adopting this technology in 2020 (source: OECD). By projecting that figure to 2023 based on the evolution of cloud spending, it is possible to estimate a penetration level for the United Kingdom of 64% in 2023.[4] That figure is well above the European mean of 45.2% reported by Eurostat for 2023. However, the UK still lies below some countries in the region such as Finland, Sweden, Norway, or Denmark (see graphic 2-2).

[3] *Source: IDC. Software and Public Cloud Services Spending Guide. This data excludes the spending in AI platforms when delivered by CSP.*

[4] *To extrapolate penetration levels for 2023, we developed a simple regression linking cloud enterprise adoption with cloud expenditure, with country and industry fixed effects. The results would suggest that a 1% increase in cloud spending is linked to an increase in cloud enterprise adoption of 0.255% (details presented in Table A-1 in Appendix A).*

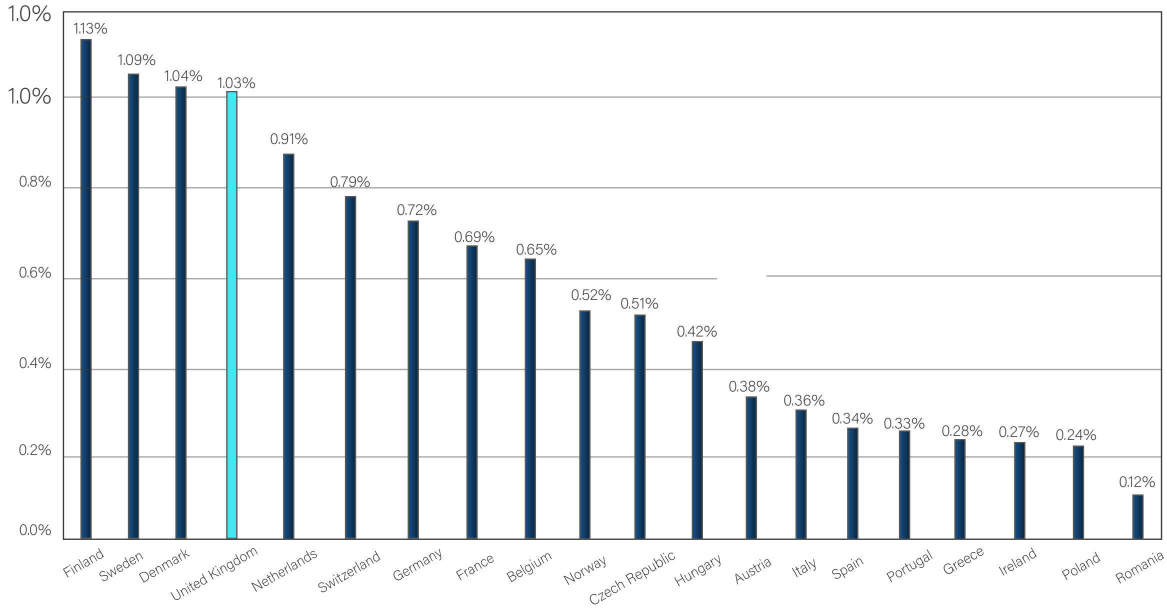
**Graphic 2-2. Europe: Cloud enterprise adoption (Percent of employer firms) (2023) (%)**




*Source: Eurostat, Telecom Advisory Services analysis.*

Correlated with cloud adoption, cloud spending as a share of GDP in 2023 in the UK is slightly below Finland, Sweden, and Denmark (see graphic 2-3).

**Graphic 2-3. Europe: Cloud spending as percent of GDP (2023) (%)**




*Source: IDC; IMF; Telecom Advisory Services analysis*

However, beyond this spending, a more significant value creation occurs through economic spillovers, which can be measured through the econometric models presented in chapters 3 and 4.

# 3. METHODOLOGY

The focus of this chapter is to assess the economic contribution of cloud computing as a technology. The empirical strategy selected for this research is supported by a theoretical model that estimates spillover effects in economic output derived from cloud enterprise adoption. The model proposed will be empirically tested for a sample of European countries, due to unavailability of enough data to estimate regression analysis only based on the UK.

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

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

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 expect TFP to depend on cloud enterprise adoption (denoted by CLOUD), and beyond it, we assume that higher artificial intelligence (AI) use will enhance cloud impact. This is reasonable, as literature suggests that both technologies are interdependent. 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 country-level time-invariant characteristics represented by a fixed effect $\Omega_i$ , capturing idiosyncratic productivity effects. In addition, $\zeta_s$ reflects sector-level unobservables that make some industries more productive than others.

As it is assumed that cloud enterprise adoption contributes to increased productivity, we expect $\Phi > 0$. Although not the focus of this study, the parameter $\delta$ will capture the specific effects of AI as interdependent to cloud[5]. Inserting equation (2) into (1), we obtain:

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

(3)

[5] *Research evidence indicates that artificial intelligence is complementary to and interdependent with cloud computing. See for example, Pop 2016), Makridakis (2017), Yang (2022), and Brynjolfsson et al. (2018), Katz et al. (2024).*

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

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

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

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

In addition, the production function can be transformed to represent productivity measures rather than overall output. Assuming constant returns to scale on capital and labour, $\alpha + \beta = 1$ 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 estimation of the productivity equation is relevant as these different output measures explain different perspectives on firm performance: while GVA is a metric of aggregate production (minus the consumption of intermediate inputs), labor productivity measures the value added for the average worker, thus representing a measure of efficiency. These models would allow us to estimate the contribution to GVA and productivity of cloud computing.

The baseline contribution of cloud to GVA is estimated through the parameter  estimated through the output equation, that represents the elasticity: a 1% increase in cloud enterprise adoption will yield an increase in GVA of . The contribution of cloud to productivity is estimated through the elasticity provided by the parameter resulting from the econometric regression of the productivity equation.

# 4. ESTIMATING THE ECONOMIC IMPACT OF CLOUD COMPUTING

## 4.1. ECONOMIC CONTRIBUTION OF CLOUD IN 2023

The aggregate economic contribution of cloud to GDP is composed of: (i) the domestic revenues generated by cloud service providers due to customer spending, 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, 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.[6] 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 4-1).

**Table 4-1. Revenue and spillover contribution of cloud services to GDP**

| ITEM | Indicator | Source |
|---|---|---|
| (1) | Cloud spending by public and private sector | From Chapter 2 |
| (2) | Spillover effect: Spill-over effect of cloud services | Calculated from elasticities in Appendix B |
| (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.[7] Considering the estimated elasticity and cloud enterprise adoption growth between 2022 and 2023, we estimated the spillovers associated to them. To reiterate from the model included in Appendix B, 1% increase in cloud enterprise adoption is associated with an increase of 0.135% of the GVA. By adding both terms, the total economic contribution of cloud computing for the UK was calculated (see table 4-2).

**Table 4-2. United Kingdom: Total economic contribution of cloud computing (2023) (in £ million)**

| ITEM | Indicator | Value |
|---|---|---|
| (1) | Cloud spending by public and private sector | £24,309.43 |
| (2) | Spillover effect: Spill-over effect of cloud services | £18,043.99 |
| (3) | Total impact of cloud services to the GDP | £42,353.42 |

*Source: Telecom Advisory Services analysis*

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[6] *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.*

[7] *The revenues derived from offering AI platforms are excluded.*

**In conclusion, the total economic impact of cloud in the United Kingdom in 2023, comprising cloud spending and its spillovers on the economy, is sizable: £42.35 billion.**

## 4.2. ECONOMIC CONTRIBUTION 2023-2030

In addition to estimating the impact for 2023 for cloud we forecast economic contribution for the seven-year interval through 2030. To estimate the spillovers from cloud enterprise adoption growth in future years, we projected cloud adoption by considering IDC forecasts on spending and the regression that links adoption and spending (see Appendix B). Aggregated values for the seven-year interval under this baseline scenario are presented in table 4-4.

**Table 4-4. United Kingdom: Economic contribution of cloud computing (2023-2030) (£ million)**

| ITEM | | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 |
|---|---|---|---|---|---|---|---|---|---|
| Cloud computing | Spending | £24,309.43 | £27,983.8 | £32,190.23 | £36,761.36 | £41,632.55 | £45,742.10 | £49,384.12 | £50,843.62 |
| | Spillover | £18,043.99 | £16,492.37 | £15,994.46 | £15,574.38 | £14,902.39 | £12,651.44 | £9,689.45 | £6,521.50 |
| | Total | £42,353.42 | £44,476.23 | £48,184.69 | £52,335.74 | £56,534.95 | £58,393.54 | £59,073.56 | £57,365.12 |
| | per worker | £1,287.81 | £1,355.61 | £1,466.82 | £1,591.20 | £1,716.73 | £1,770.96 | £1,789.36 | £1,735.45 |

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

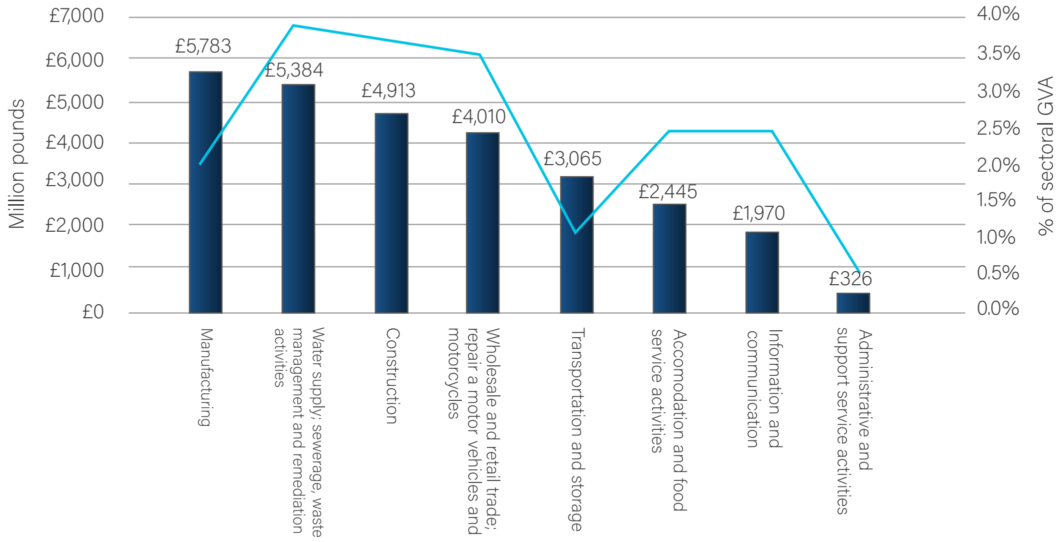
**During the seven-year timeframe (2024-30), the economic impact of cloud in the United Kingdom will be significant, reaching £ 376 billion, representing 1.91% of the forecasted cumulative GDP. In terms of productivity, the economic gains due to cloud computing account for £ 1,287.81 per worker in 2023, increasing to £ 1,735.45 in 2030.** The decline in economic impact in 2030 is driven by a decrease in the cloud penetration growth rates, a driver of spillovers, in that year.

## 4.3. ESTIMATING ECONOMIC IMPACT BY SECTOR

Based on the estimates presented above for 2023, we estimated the differential economic impact across industries. Strictly speaking, differences in economic impact could be traced back to the variance in cloud adoption, on the number of firms adopting cloud by sector, and on the growth rates of cloud spending.

The estimates were calculated for a selected list of industrial sectors as represented in Graphic 4-2. Results suggest the largest economic impact in the wholesale and retail trade, construction, and information and communication sectors. As a share of the sector GVA, it is in the construction sector where the largest effects are found (3.6% of its GVA). Lowest impact levels are identified for the water supply industries.

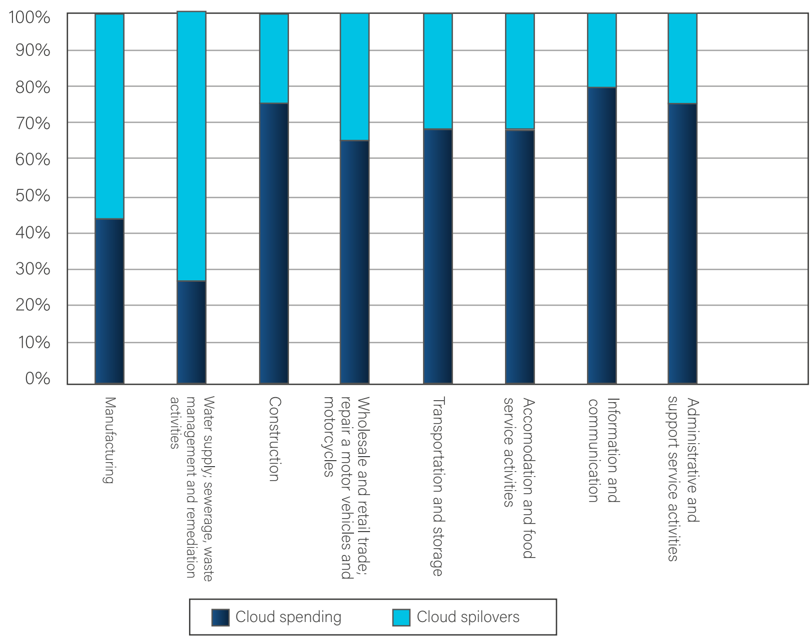
**Graphic 4-2. United Kingdom: Economic impact of Cloud Computing in selected sectors (2023)**




*Source: Telecom Advisory Services analysis*

However, the composition of the effect in each sector varies largely, depending on the growth rate of adoption levels, and the number of firms adopting cloud (Graphic 4-3).

**Graphic 4-3. United Kingdom: Economic impact of Cloud Computing in selected sectors by source of impact (2023)**




*Source: Telecom Advisory Services analysis*

In some industries, the main contribution is linked to direct spending (e.g.: construction), while in other sectors, the spillovers are the main source of economic impact (manufacturing).

# 5. CONCLUSIONS

The purpose of this study has been to assess the economic contribution of cloud computing in the United Kingdom. The United Kingdom is the most mature European cloud computing market, accounting for £ 24 billion in 2023 and representing the 23% of the total spending of the continent.

The estimated empirical models conducted for the United Kingdom allow us to draw the following conclusions:

- **The total economic impact of cloud in the UK in 2023, comprising cloud spending and its spillovers on the economy, accounts for £ 42.35 billion pounds.**
- **In terms of productivity, the economic gains in 2023 due to cloud computing accounts for £ 1,287.81 per worker.**
- **The average seven-year economic contribution of cloud for the UK projected for the period 2023-2030 is significant, accounting for 1.91% of the GDP.**
- **In some industries, the main contribution is linked to direct spending (e.g.: construction), while in other sectors, the spillovers are the main source of economic impact (manufacturing).**

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# APPENDIX A. LINK BETWEEN CLOUD SPENDING WITH ENTERPRISE ADOPTION

**Table A-1. Fixed Effects estimate linking cloud enterprise adoption with spending**

| | |
|---|---|
| Dep. var.: log (CLOUD) | |
| Log (CLOUD REVENUE) | 0.255*** |
| | [0.042] |
| Country Fixed Effects | YES |
| Sector Fixed Effects | YES |
| Observations | 199 |
| R-squared | 0.918 |

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

# APPENDIX B. DATASET AND ECONOMETRIC RESULTS

## B.1. THE DATASET

The sample for the econometric analysis consists of 9 economic sectors across 26 European countries during the year 2021. 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 service activities
- Administrative and support service activities
- Construction
- Information and communication
- Manufacturing
- Professional, scientific, and technical activities
- Transportation and storage
- Wholesale and retail trade; repair of motor vehicles and motorcycles
- Water supply; sewerage, waste management and remediation activities

*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 Value Added (in current million euros) | tat |
| K | Total fixed assets (net)-- current replacement costs, million | Eurostat |
| L | Total employment (thousands of jobs) | Eurostat |
| CLOUD | Cloud enterprise adoption (business purchasing cloud services every 100 enterprises).<br>Missing values addressed through industry averages. | Eurostat |
| CLOUD PRICE | Cloud ARPU (as a share of average revenue per firm) | Statista / Eurostat |
| CLOUD REVENUE | Cloud ARPU multiplied per the number of firms using cloud services (in current million euros) | Statista / Eurostat |
| CLOUD COMPANIES | Cloud companies per million inhabitants | Crunchbase / TAS |
| AI | AI penetration, measured as enterprises using AI services (every 100 enterprises).<br>Missing values addressed through industry averages. | Eurostat |
| AI PRICE | AI ARPU (as a share of average revenue per firm) | Statista / Eurostat |
| AI REVENUE | AI ARPU multiplied per the number of firms using AI services (in current million euros) | Statista / Eurostat |
| AI COMPANIES | AI companies per million inhabitants | Crunchbase / TAS |
| SOFTWARE ERP | Enterprises using ERP software (every 100 enterprises) | Eurostat |
| SOFTWARE CRM | Enterprises using CRM software (every 100 enterprises) | Eurostat |
| URBAN | Urban population (%) | World Bank |
| HK | Enterprise employed ICT/IT specialist (%) | Eurostat |

*Source: Telecom Advisory Services analysis*

Most variables are extracted from Eurostat. The AI variables to be used for the purpose of the interaction with cloud are specified as a dummy depending on the relative position of each observation in the overall distribution of AI use. From this perspective, the sample is divided into two. We identify a dummy variable named "AI > mean", taking values of 1 in all cases in which the observation relies above the median of the distribution of AI adoption (0 in other case). The baseline scenario, the firms with low AI use, are those situated below the median.

Two approaches were used to test the interdependent economic impact of AI and cloud: (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 OLS single-equation estimations.

### B.2. FIXED EFFECTS OLS MODEL

Table B-3 presents the results for the fixed effects estimate of the output and productivity equations, with robust standard errors clustered at the country-level. We first assume cloud and AI to be exogenous. All estimates include country and sector fixed effects.

**Table B-3. Fixed Effects estimate of output and productivity equations**

| Dep. var.: log(Y) | log(Y) | log(Y/L) |
|---|---|---|
| log(K) | 0.285*** | |
| | [0.053] | |
| log(K/L) | | 0.295*** |
| | | [0.051] |
| log(L) | 0.647*** | |
| | [0.077] | |
| Log (CLOUD) | 0.135* | 0.145* |
| | [0.079] | [0.080] |
| Log (CLOUD)#AI > MEDIAN | 0.043*** | 0.044*** |
| | [0.014] | [0.014] |
| AI | 0.002 | 0.001 |
| | [0.005] | [0.005] |
| Country Fixed Effects | YES | YES |
| Sector Fixed Effects | YES | YES |
| Observations | 185 | 185 |
| R-squared | 0.985 | 0.920 |

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

The results reported in the first column of Table B-3 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 below).

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. The baseline scenario (low AI use) represents the case of lower economic impact from cloud computing.

According to this estimation, **a 1% increase in cloud enterprise adoption is associated with an increase of 0.135% of the GVA, regardless of the level of AI use. For those observations with higher than median AI use, the elasticity increases to 0.178% (resulting from adding the baseline coefficient of 0.135 plus the effect associated to the AI > MEDIAN variable, 0.043).**

In the second column of Table B-3 we present the results for the productivity equation. In this case, the estimates present a slightly worse, although still acceptable, model fit.

The results verify again the economic relevance of cloud enterprise 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 estimated for the output equation.

## B.3. 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-4).

**Table B-4. System of simultaneous equations**

| | | |
|---|---|---|
| Aggregate production equation | | $Y_{it} = f(K_{it}, L_{it}, CLOUD_{it}, AI_{it})$ |
| Cloud equations | Demand equation | $CLOUD_{it} = g(\text{[illegible]}, CLOUD\ PRICE_{it}, HK_{it}, SOFTWARE_{it}, URBAN_{it})$ |
| | Supply equation | $CLOUD\ REVENUE_{it} = h(CLOUD\ PRICE_{it}, Y_{it}, CLOUD\ COMP_{it})$ |
| | Cloud infrastructure production | $\Delta CLOUD_{it} = j(CLOUD\ REVENUE_{it})$ |
| AI equations | Demand equation | $AI_{it} = k(\text{[illegible]}, AI\ PRICE_{it}, HK_{it}, SOFTWARE_{it}, URBAN_{it})$ |
| | Supply equation | $AI\ REVENUE_{it} = s(AI\ PRICE_{it}, Y_{it}, AI\ COMP_{it})$ |
| | AI infrastructure production | $\Delta AI_{it} = z(AI\ REVENUE_{it})$ |

*Source: Telecom Advisory Services analysis*

In this case, cloud demand ($CLOUD_{is}$) is expected to depend on the average income per firm ($Y/FIRM_{is}$), on cloud prices ($CLOUD\ PRICE_{is}$), on the degree of human capital ($HK_{is}$), 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 ($CLOUD\ COMP_{is}$). Finally, the variation in cloud enterprise adoption ($\Delta CLOUD_{is}$)is modelized to depend on cloud output ($CLOUD\ REVENUE_{is}$). A similar approach is taken for the AI-related equations.[9]

Results for the output equation and productivity equations are presented in Table B-5. The estimation is conducted through 3-Stage Least Squares (3SLS) simultaneous equation approach. In both estimates we are including country and sector fixed effects in the main equation.

**Table B-5. 3SLS estimate of simultaneous equation model**

| Dep. var.: | log(Y) | log(Y/L) |
|---|---|---|
| log(K) | 0.283*** | |
| | [0.034] | |
| log(K/L) | | 0.294*** |
| | | [0.033] |
| log(L) | 0.659*** | |
| | [0.057] | |
| Log (CLOUD) | 0.393** | 0.350* |
| | [0.190] | [0.189] |
| Log (CLOUD)#AI > MEDIAN | 0.031** | 0.033** |
| | [0.015] | [0.015] |
| AI | 0.002 | 0.002 |
| | [0.005] | [0.005] |
| Dep. var.: log (CLOUD) | | |
| Log (CLOUD PRICE) | -0.362*** | -0.358*** |
| | [0.061] | [0.061] |
| Log (Y/FIRM) | 0.067 | 0.064 |
| | [0.052] | [0.052] |
| Log (SOFTWARE ERP) | -0.022 | -0.022 |
| | [0.092] | [0.092] |
| Log (SOFTWARE CRM) | 0.312*** | 0.316*** |
| | [0.106] | [0.106] |
| Log(URBAN) | 0.659*** | 0.656*** |

[9] *Variables ($\Delta CLOUD_{is}$) and ($\Delta AI_{is}$) are designed as the ratio between penetration and the respective country average.*

| | | |
|---|---|---|
| | [0.221] | [0.221] |
| Log (HK) | 0.061 | 0.062 |
| | [0.089] | [0.089] |
| Dep. var.: log (CLOUD REVENUE) | | |
| Log (CLOUD PRICE) | 0.903*** | 0.921*** |
| | [0.037] | [0.035] |
| log(Y) | 0.963*** | 0.994*** |
| | [0.042] | [0.035] |
| CLOUD COMPANIES | 0.180*** | 0.178*** |
| | [0.032] | [0.031] |
| Dep. var.: log(ΔCLOUD) | | |
| Log (CLOUD REVENUE) | 0.084*** | 0.085*** |
| | [0.022] | [0.022] |
| Dep. var.: log (AI) | | |
| Log (AI PRICE) | -0.453*** | -0.451*** |
| | [0.124] | [0.124] |
| log(Y/FIRM) | 0.022 | 0.021 |
| | [0.112] | [0.112] |
| Log (SOFTWARE ERP) | 0.344** | 0.342** |
| | [0.145] | [0.144] |
| Log (SOFTWARE CRM) | 0.295* | 0.297* |
| | [0.158] | [0.158] |
| Log (URBAN) | 0.332 | 0.338 |
| | [0.336] | [0.336] |
| Log (HK) | -0.134 | -0.132 |
| | [0.133] | [0.133] |
| Dep. var.: log (AI REVENUE) | | |
| Log (AI PRICE) | 0.813*** | 0.823*** |
| | [0.095] | [0.088] |
| log(Y) | 0.970*** | 1.011*** |
| | [0.106] | [0.084] |
| AI COMPANIES | 0.022 | 0.021 |
| | [0.029] | [0.029] |

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

In the first column of Table B-5 we estimate the output model. The results for the main equation are in line with the expectations, with cloud computing presenting a positive and significant effect. The elasticity is higher than in the model that presented in section B.2, Therefore, for conservative purposes, we will take as the valid reference the elasticities reported in Table B-3.

As for the remaining equations, results are in line with the expectations. Particularly, cloud demand depends positively on the degree of firm's CRM software use, while it depends negatively on the service price. The coefficient for income per firm is not significant, suggesting demand insensitiveness to income differentials. In addition, both income, prices and number of providers 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 penetration levels with respect to the respective country average, as expected.

As for the AI-related equations, demand seems to depend positively on firm's software use (both CRM and ERP), while the coefficient for price is negative and significant. As for AI revenue, it depends positively on prices and income. Finally, the larger the expenditure in AI, the bigger the variation of penetration levels with respect to the respective country average, as expected.

In the second column of Table B-5 we turn to the labor productivity estimate. The estimated $\alpha$ 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.

## B.4. CONCLUSIONS

The results presented above provide robust evidence of the significant effect that cloud computing has on economic output and productivity levels. The coefficients generated in the econometric model specified section 4.1 will be used to calculate the economic contribution of cloud for 2023.