Telecom Advisory Services

ECONOMETRIC STUDY FOR ESTIMATING THE ECONOMIC IMPACT OF **DATA CENTER INFRASTRUCTURE**

General Model

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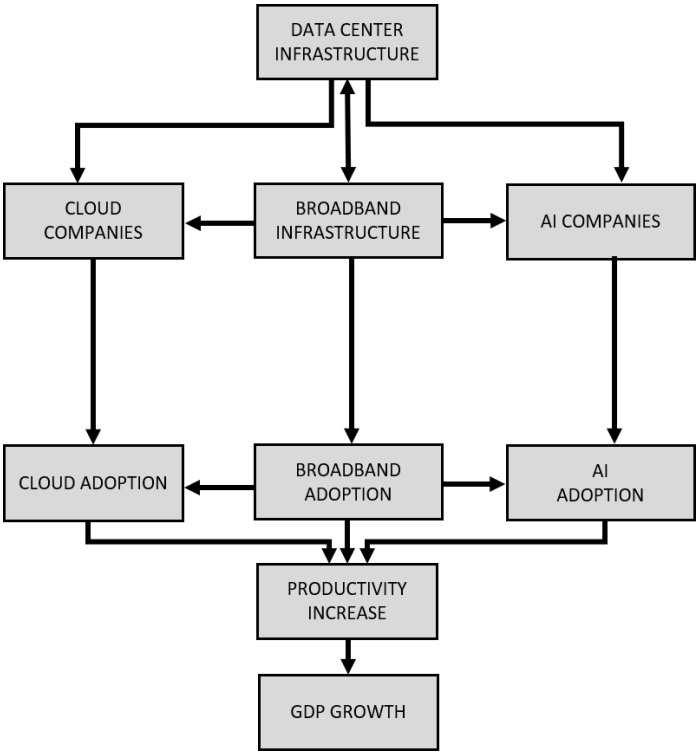
EXECUTIVE SUMMARY

The focus of this study is to estimate the economic impact of data center deployment. As such, it aims at filling a gap in the research literature regarding the spillover contribution of data centers in areas such as productivity, economic growth, employment and consumer surplus. The theoretical framework underlying this research is based on the formalization of multiple direct and indirect effects generated by data center infrastructure within a causality chain:

- Data center deployment stimulates the entry and development of digital service providers, such as cloud and artificial intelligence (AI) companies, for which it will be more attractive to set up facilities in countries with better conditions for data storage and processing. This causal link is critical because countries that want to supply digital services locally depend on large data centers as their infrastructure.
- The development of data centers is also expected to stimulate the deployment of broadband transport networks required to facilitate access to their facilities.
- The increase in cloud and AI services, combined with broadband coverage, drives an increase in the adoption of cloud computing and AI by enterprises and broadband adoption by the population at large.
- The adoption of cloud, AI and broadband yields a positive productivity spillover.
- Simultaneously, the increased adoption of broadband yields the additional use of multiple digital services, which drives consumer surplus.
- The increased adoption of digital services may also have employment effects that can turn out to be either negative (if job-displacement effects dominate) or positive (if compensatory effects dominate).
- Overall economic impact will depend on how much productivity increases, on how employment levels are affected, and on potential negative externalities arising from increases in electricity prices.

Figure A describes the causal relationships and conditioning factors in each step of the causal chain, leading from data center deployment to economic impact (productivity, employment, GDP growth, and consumer surplus).

Figure A. Diagram of causal effects associated with data center deployment



Source: Telecom Advisory Services

A reduced form of the diagram presented above is estimated through econometric models built to quantify the impact of data centers on productivity, employment and GDP growth for a sample of 39 countries around the world. In addition, the contribution to consumer surplus was measured through an adjusted measure of willingness to accept compensation for giving up ten digital services.

The multiple effects identified can be quantified in terms of elasticities as follows:

Table B. Impact of data center deployment in an average country

Model	Item	Hypothesis	Claim
Reduced form specification	1	Data centers → Cloud penetration	• A 1% increase in cloud zone capacity raises cloud adoption by 0.0571% (*)
	2	Data centers → AI penetration	• A 1% increase in cloud zone capacity raises AI adoption by 0.5891% (except in ADCs) (*)
	3	Data centers → BB penetration	• A 1% increase in cloud zone capacity raises FBB adoption by 0.0176% (*) • A 1% increase in cloud zone capacity raises MBB adoption by 0.0145% (*)
	4	Digital adoption → Productivity	• A 1% increase in cloud zone capacity raises labor productivity by 0.0136% in LDCs and MDCs (0.0020% in ADCs) • A 1% increase in cloud zone capacity raises TFP by 0.0129% in LDCs and MDCs (0.0019% in ADCs)
Employment	5	Digital adoption → Employment	• A 1% increase in cloud zone capacity reduces employment by 0.0056% in LDCs and MDCs (0.0008% in ADCs), although in the following years employment levels are recovered.

Model	Item	Hypothesis	Claim
Mechanisms	6	Data centers → Digital companies	• A 1% increase in cloud zone capacity raises the number of cloud companies by 0.0105% (*) • A 1% increase in cloud zone capacity raises the quantity of AI companies by 0.1178% (*) • A 1% increase in cloud zone capacity raises the quantity of Big Data companies by 0.0496% (*) • A 1% increase in cloud zone capacity raises the quantity of Fintech companies by 0.0066% (*)
	7	Data centers → BB infrastructure	• A 1% increase in cloud zone capacity raises FTTH coverage by 0.0172% (*) • A 1% increase in cloud zone capacity raises FBB speeds by 0.0216% (*) • A 1% increase in cloud zone capacity raises MBB speeds by 0.1180% (*)
Negative externality	8	Data centers → Electricity price	• A 1% increase in cloud zone capacity raises electricity prices by 0.0943% (*)
	9	Electricity price → Investment	• A 1% increase in cloud zone capacity reduces investment by 0.0006%
End-to-end effects		Data centers → GDP	• A 1% increase in cloud zone capacity increases GDP by 0.0113% in LDCs and MDCs (0.0011% in ADCs) (*)
Consumer surplus		Data centers → increase in consumer surplus due to adoption of digital services	• The deployment of digital services triggered by an increase in cloud zone capacity will increase consumer surplus resulting from an increase in adoption of digital services

Note: (*) effects that take place with a one-year lag. Baseline values for the calculation of these elasticities are those of the average country in the sample.
LDCs: Less developed countries (up to 33p of income per capita in the first year of sample)
MDCs: Moderately developed countries (33p-66p of income per capita in the first year of sample)
ADCs: Highly developed countries (from 66p of income per capita in the first year of sample)
Source: Telecom Advisory Services analysis

I. INTRODUCTION

The objective of this study is to assess the economic impact of data center deployment. While empirical studies conducted to date independently confirm the positive impact of digital technologies on the economy (in particular, broadband, cloud computing, and even artificial intelligence), evidence is still scarce regarding the understanding of how data centers contribute to economic growth. For example, research on the contribution of broadband to GDP has already produced significant evidence over the past two decades. Similarly, the provision of public cloud services in combination with broadband networks has also been shown to drive GDP and labor productivity growth. However, so far there is limited research that addresses the economic impact of data center infrastructure.

Data centers are conceived as the necessary components to support the digital economy through the storage, manipulation and use of data, being, in short, the industrial base of the future. However, as demonstrated in the review of the research literature presented in this report, the analytical work conducted to date on the economic impact of data centers focuses on their short-term contribution to areas such as job creation resulting from construction and operations, or local taxes. In fact, contrary to the extensive research on the economic effects of public infrastructure such as roads and telecommunications, no work exists yet about the spillover contribution of data centers in areas such as productivity, innovation or new business creation. The purpose of this report is to fill that void.

The main focus of this work is to quantify the economic impact of large data centers built by public cloud service providers, neoclouds and AI factories to offer data storage and processing services, as well as applications (especially training of and inference with artificial intelligence models) to companies and governments. While not the main focus of this study, we acknowledge that data processing infrastructure also includes colocation facilities and smaller data centers (such as those installed by companies and government agencies to support them in data processing) and servers (both those used by public and private organizations to support the processing of their data, and those deployed to be used by digital platforms and Internet services).

The central hypothesis of the study states that large public data centers deployed by cloud service providers, neoclouds and AI factories stimulate the development of a country's digitization, particularly regarding the adoption of cloud computing and artificial intelligence. This, in turn, results in a significant economic contribution through productivity spillovers, which will yield gross domestic product (GDP) growth and job creation.

The remaining chapters of the document are organized as follows. Chapter II summarizes the literature review on the study of the economic impact of infrastructure. It concludes by highlighting the significant gap in the research on the role of data centers in driving economic gains. Chapter III presents a theoretical framework and a series of causal models that serve to estimate the association of large public data centers with other variables linked to digital development, and, through these, their impact on productivity levels and GDP growth. Chapter IV

presents the theoretical framework and methodology for measuring consumer surplus. Chapter V presents the database used to build the empirical estimation of the econometric models, as well as a preliminary descriptive-exploratory analysis, complemented with the main correlations between the variables of interest. Chapter VI presents the results of econometric models. Chapter VII presents the conclusions of the study. Finally, the bibliography and methodological appendices are included at the end of the paper.

II. DOES DATA CENTER DEPLOYMENT GENERATE ECONOMIC IMPACT? A REVIEW OF THE LITERATURE

The issue of the economic effects of data center deployment should be considered within the research tradition which started examining the impact of public infrastructure on economic growth. This body of work is composed of four clearly defined research clusters:

- Economic growth associated with the deployment of public infrastructure, such as roads, railways, and the like.
- Output effects resulting from the deployment of network infrastructure, such as telecommunications, particularly broadband.
- Economic contribution of production infrastructure, such as manufacturing facilities.
- Short-term economic impact of data infrastructure, in particular data centers.

Within the first research body, the macroeconomic literature has generated substantial empirical support, albeit not totally consistent, regarding the economic impact of general infrastructure. Research on aggregate output was initiated by Aschauer (1989), who relied on an endogenous growth model linking the productivity slowdown in the United States to the decline in infrastructure investment. While further research results did not totally support this conclusion (particularly the magnitude of the impact, as documented by Holtz-Eakin, 1994; Cashin, 1995, and Baltagi and Pinnoi, 1995), it is fair to conclude that more recent results have confirmed the contribution of public infrastructure to economic output (Canning, 1999; Calderon and Serven, 2017). For example, Fernald (1999) finds high productivity generated by the deployment of additional roads in the United States. The effects of public infrastructure were also quantified in terms of their contribution to manufacturing employment and agricultural productivity (Kline and Moretti, 2014).

Within the second research cluster, a substantial body of research validated the impact of network infrastructure, which comprises telecommunications (Roller and Waverman, 2001), and, more specifically, broadband networks on GDP (ITU, 2012; Katz and Jung, 2021; De Clercq et al., 2023; Briglauer et al., 2023a; Bertschek et al., 2015), productivity (Cardona et al., 2013; Gallardo et al., 2021), job creation (Hjort and Poulsen, 2019; Simione and Li, 2021; Isley and Low, 2022) and firm performance (Viete and Erdsiek, 2020). In particular, network infrastructure deployment has been shown to yield a positive economic contribution due to three effects: economies of scale, network externalities and competitive acceleration. For example, research on broadband internet indicates that economic impact is associated with returns to scale (Koutroumpis, 2009). Furthermore, by enabling improved access, network infrastructure facilitates regional connectivity by lowering costs and, ultimately, facilitating market access (Briglauer and Gugler, 2019).

The study of the economic impact of production infrastructure, the third research cluster, was launched to understand the contribution of manufacturing facility

deployment to local economies. The interest in this research body was related to the need to understand the effect of the potential local promotion subsidies aimed at the development of specific geographies. This research body was initiated by Greenstone and Moretti (2003) to study the effect of investment in large manufacturing plants on local economies. For example, the authors determined that investment in large production facilities yielded a significant increase in property values. In a later study, Greenstone et al. (2010) also verified productivity gains of 12% as a result of the deployment of large factories, suggesting the action of agglomeration spillovers over the economies under consideration. Multipliers were also extended to job creation (Moretti, 2012).

While the prior three research bodies focused on long-term effects and spillovers (such as impact on productivity or GDP growth), research on data center economic contribution, the fourth cluster, has focused to date primarily on short-term effects. This is not surprising since a lot of the public debate on data centers has so far centered on the local impact on sustainability (e.g., energy consumption) of data center deployment, and the need to deploy subsidies to promote their local deployment. For example, Yue and Zeng (2026) relied on a difference-in-differences methodology to measure the local economic effects of data center deployment in United States counties. Their analysis concludes that data center launch increases local employment by 3.5%, wages by 5.0%, business creation by 4.7%, and median household income by 1.9%, while reducing unemployment. These effects could be verified in metropolitan areas that capitalize on agglomeration multipliers to generate employment gains of 4.1%.

These findings are fairly consistent with those of Alvarez et al. (2026), who study the impact of data center deployment on local US counties, as well. By relying on instrumental variables to address endogeneity concerns, the analysis identified positive effects on employment (total, data-processing, and construction), expansion in local business establishments, increases in house prices, adjusted gross income and wages, among other effects. According to the authors, the most important effect occurs through the creation of data processing jobs.

The local job creation multiplier effect, identified in the two prior studies, was validated by Bontadini et al. (2026) with an OLS approach applied to French commuting zones. The authors conclude that a data center deployment will trigger a 0.6% increase in total employment, although job creation is concentrated in non-tradable sectors and specialized business services, with high-skilled jobs combined with a displacement effect in middle- and low-skilled occupations.

In addition to the econometric approach, several pieces of research relying on either descriptive multipliers or input-output analysis have been generated to estimate the short-term construction vs. operational jobs created as a result of data center deployment. In particular, Hicks (2025) compiled five case studies (see Table II-1).

Table II-1. Input-output models of data center impact

Study	Location	Direct construction jobs	Direct operational jobs	Total employment (including multipliers)	Methodology
PwC (2023)	USA effects at each site	1,000-10,000 per hyperscaler campus (varies by project)	50-300 per campus	6*direct jobs	Descriptive with multipliers
JLARC (2024)	Virginia	3,000-5,000 (construction phase)	100-400 (long-run operational)	6,000-8,000	Descriptive with multipliers
Sage Policy (2024, 2024a)	Frederick County, MD	~2,000	~200	3,000-4,000	IMPLAN multipliers
Thompson (2019)	Sarpy County, NE	~1,200 (154 per data center)	100-150 (37 per data center during operations)	~2,000	Descriptive with multipliers
Morrow County, OR (2024)	Morrow County, OR	1,500	80-120	~2,500	IMPLAN scenario modeling; not causal

Source: Hicks, M. (2025). Data centers and local job creation: Some preliminary causal estimates from Texas

In sum, the survey of the literature indicates that, while the impact of public, network and production infrastructure has been extensively studied, there is no available quantitative research on the effects on productivity, economic growth, or innovation from data center investment (see Table II-2).

Table II-2. Summary of relevant findings on economic impact of infrastructure

	Short-term impact	Aggregate effect on output, productivity
Public Infrastructure		• Electricity generating capacity and transportation networks have roughly the same marginal productivity as capital as a whole (Canning (1999) • National road infrastructure drove productivity increases (1999) • Fernald, Increases in manufacturing employment and agricultural productivity (Kline and Moretti (2014)
Network infrastructure		• A 10% increase in FTTx connections leads to an (incremental) increase in the GDP of around 0.02–0.03% in the OLS estimation and 0.02–0.04% in the IV case (controlling for basic broadband with corresponding estimates of 0.024-0.026% in the IV case (Briglauer and Gruber, 2019) • An increase in mobile broadband adoption by 10% increases GDP per capita by 2.04% (in low-income countries) and by 1.62% (in middle-income countries) (Katz and Jung, 2021)
Production infrastructure	• Increases in property values (Greenstone et al, 2010) • Multipliers were also extended to job creation (Moretti (2012)	• Productivity gains (Greenstone et al., 2010)
Data infrastructure (data centers)	• Increases in jobs, wages, business establishments, and household income (Yue and Zeng, 2026) • Positive effects on employment (total, data-processing, and construction), expansion in local business establishments, increase in house prices, and adjusted gross income, and wages (Alvarez et al., 2026)	• The deployment of multiple centers can yield economic growth through spillovers from data stored in data centers as a non-depletive and non-rival capital asset (not quantified through modelling)

Source: Compiled by the authors

In this context, analogous to the research conclusion that public, network and production infrastructure contribute to economic growth, it is relevant to ask what the effect would be in the case of data centers. This is particularly relevant because, in addition to short-term benefits in terms of employment gains and taxes, research on the effects of data centers points to some short-term negative externalities that need to be balanced against a longer-run perspective. For example, Alvarez et al. (2026) indicate that data center deployment is associated with an increase in local commercial electricity tariffs which, combined with rising housing costs, act as an indirect tax on local non-data center businesses, thereby reducing their competitiveness.

Furthermore, on the matter of job creation, current research tends to extrapolate short-term effects and draws conclusions for the long term with little analysis of spillover dynamics as driven by effects such as innovation or new business creation.[1] Furthermore, research in some cases does not differentiate between hyperscaler and colocation data centers, rendering conclusions of employment effects meaningless. For example, Bahar and Wright (2026) demonstrate that, while hyperscale data centers drive large information sector job gains, colocation facilities have negligible impact.

Most importantly, despite the rush of local communities to provide subsidies to stimulate data center location, there are no studies that estimate their overall economic effects. Along these lines, in part driven by the local community impact assessment needs (e.g., how much local tax revenue will be generated by the data center deployed?), no analysis exists that considers the spatial geographic impact driven by regional externalities (e.g., what is the economic contribution in areas surrounding the area where the center is deployed?). Interestingly enough, two studies were found in the literature review that shift the axis of economic impact from immediate job creation and taxes to long-term technological spillovers and industrial modernization.

Chen and Fan (2026) rely on commercial data center license records from China's Ministry of Industry and Information Technology (MIIT) and AI patent applications from 2015 to 2023 to conduct an analysis of infrastructure impact on innovation. They find that a greater presence of data centers at the city level boosts corporate AI patenting through mechanisms linked to digital transformation and the attraction of technical talent to cities with such infrastructure. The primary explanatory variable in their study is the accumulated stock of commercial Internet Data Center (IDC) licenses in each city. The study's main specification employs a panel model with firm and year fixed effects, along with firm- and city-level controls and standard errors clustered by firm. To address potential endogeneity issues—specifically the possibility that data centers are located precisely where technological activity is already high—the authors use the provincial industrial electricity price as an instrument. Higher electricity prices increase data center operating costs and

[1] As an example, Goetzel et al. (2026) conclude that "the standard data center development model—speedy dealmaking and opaque negotiations— delivers short-term construction jobs and revenue, but little durable local economic upside," without providing ex post analysis of impact on innovation, new business creation and the like.

discourage their location in a given area, yet—once controls and fixed effects are included—these prices should not directly affect corporate AI patenting.

In a second case of economic impact of data centers, Yülek et al. (2017) focus not on a local community but on a country (Turkey), addressing the question of whether the deployment of "a data center region" (that is to say, multiple centers) can yield economic growth. For this purpose, rather than focusing on infrastructure, they mention the need to conduct spillover analysis using data stored in data centers as a non-depletive and non-rival capital asset. That being said, the remainder of their analysis is based on an input-output approach to quantify construction effects.

In conclusion, to fill the gap in the research, the main focus of this report is to quantify the long-term economic impact of large data centers built by public cloud service providers to offer data storage and processing services, as well as the training of and inference with artificial intelligence models for companies and governments.

III. THEORETICAL FRAMEWORK TO FORMALIZE THE ECONOMIC IMPACT OF DATA CENTER DEPLOYMENT

The theoretical framework underlying this research is based on the formalization of multiple direct and indirect effects generated by data center infrastructure, as well as the conditioning factors that link data center deployment to economic spillovers:

- Data center deployment stimulates the development of digital service providers, such as cloud and AI companies, for which it will be more attractive to set up facilities in geographic locations with better conditions for data storage and processing. This causal link is critical because countries that want to develop local cloud and artificial intelligence depend on large data centers as their infrastructure.
- The development of data centers is also expected to stimulate the deployment of broadband transport networks to facilitate access to their facilities; at the same time, when broadband networks are more developed, they promote the deployment of data centers.
- The increase in cloud and AI services, combined with broadband coverage, drives an increase in adoption of cloud and AI by enterprises and broadband adoption by the population at large.
- The stimulus in the adoption of broadband and digital services yields a positive productivity spillover.
- The increased adoption of digital services may also have employment effects beyond the pure construction stimulus that can turn out to be either negative (if job-displacement effects dominate) or positive (if compensatory effects dominate).
- Overall economic impact will depend on how much productivity increases and how employment levels are affected.
- Furthermore, data center deployment contributes to the adoption of digital services, which, in turn, enhance overall consumer surplus.

These multiple relationships are presented next in Figure III-1.

First causal relationship: data center infrastructure is expected to stimulate the development of digital industries, because it will be more attractive for them to develop in countries with better conditions for data storage and processing facilities. Digital industries are defined as companies that offer services that go beyond connectivity, such as cloud computing or AI solutions. These companies require the processing and storage capacity of large data centers in order to offer their services to retail consumers and firms.

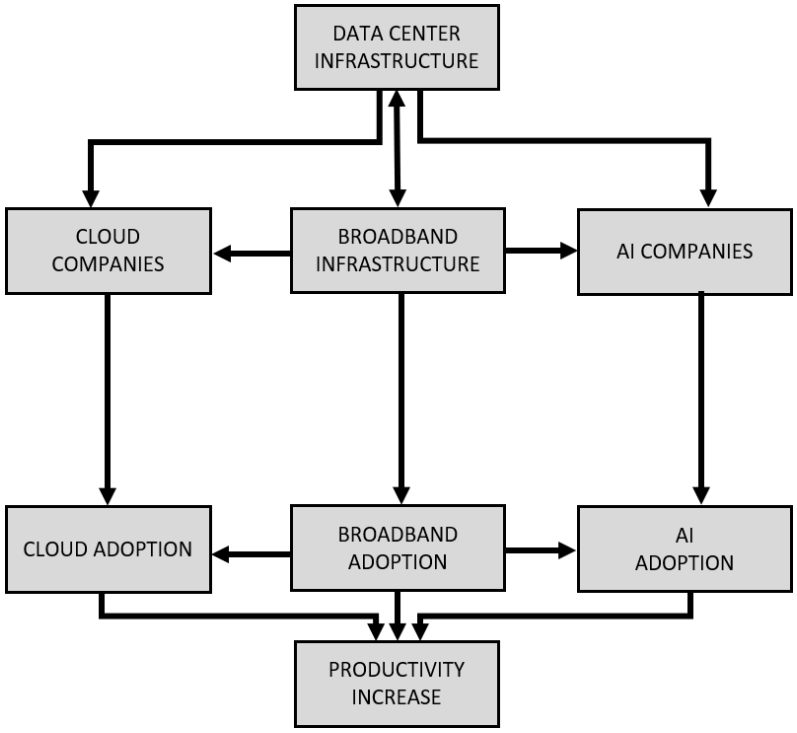
Second causal relationship: it is also assumed that a relationship exists between data centers and broadband infrastructure. This implies that the development of data centers incentivizes the deployment of transport networks for data, while the inverse effect may also take place: when broadband networks are more developed, they stimulate the deployment of data centers.

Third causal relationship: we estimate that enterprise adoption of digital services (such as cloud computing and AI) depends, respectively, on the level of development

of broadband infrastructure and the presence of digital companies offering services at the local level.

Fourth causal relationship: as demonstrated by existing research (cited in the prior chapter), a higher level of adoption of broadband and other digital services (cloud and artificial intelligence) should contribute to productivity spillovers, therefore driving economic growth.

Figure III-1. Diagram of causal effects associated with data center deployment



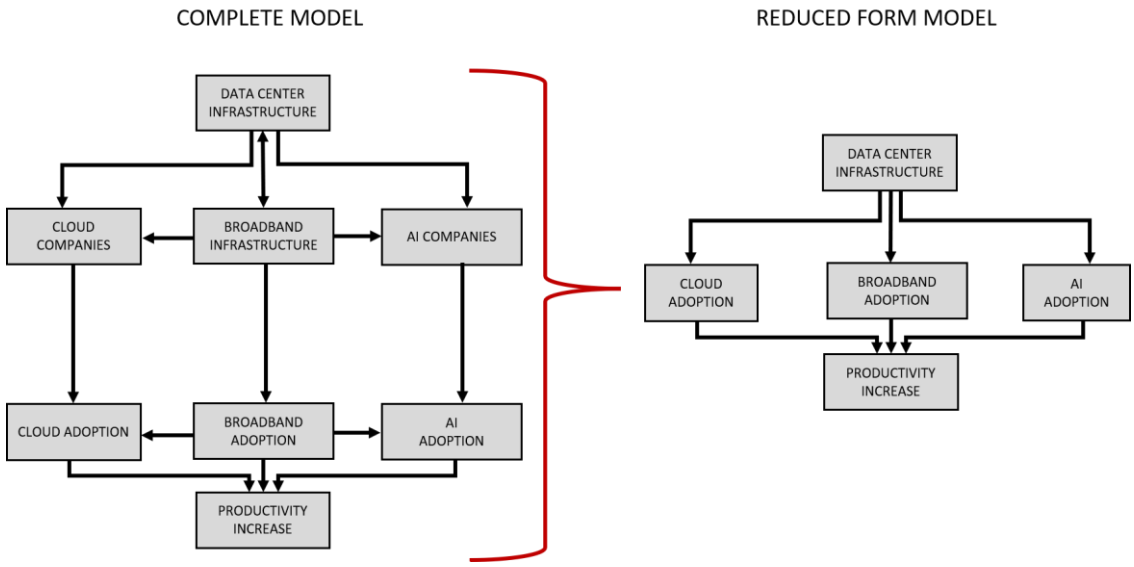
Source: Telecom Advisory Services analysis

The structural system depicted in Figure III-1 contains endogenous relations that must be considered in the empirical specification. This means that the econometric estimates will have to be conducted through an instrumental variables (IV) approach. However, the presence of bidirectional links and a large number of cross-dependencies (from broadband infrastructure to cloud and AI companies, and from broadband adoption to cloud and AI adoption) complicates the identification strategy. Estimating it as a system requires exclusion restrictions and valid instruments for each equation, and these are rarely available at the country level. On the other hand, reusing similar sets of instruments for downstream outcomes can violate the exclusion restriction. This requires the assumption that instruments affect downstream technology adoption exclusively through local data center presence, something that may not necessarily be the case.

Therefore, for empirical purposes, we propose an alternative reduced-form approach (Figure III-2). This consists in running a reduced-form equation linking

the main digital adoption variables directly to cloud data centers. In a second layer, we link digital adoption measures to productivity increases. Each layer will be estimated using different sets of instrumental variables. The reduced form collapses the linkages presented in Figure III-1 into a single, recursive structure (infrastructure → adoption → productivity), which facilitates identification. On the other hand, the reduced form estimates the total effect of data center infrastructure on productivity, rather than a partial effect that depends on arbitrary conditioning such as the intermediate paths that take place through cloud and AI companies and broadband infrastructure.

Figure III-2. Diagram of reduced-form approach to be empirically estimated



Source: Telecom Advisory Services analysis

The hypotheses to be tested empirically are described in Table III-1 below.

Table III-1. Hypotheses to be tested

Model	Item	Hypothesis
Reduced form specification	1	Data centers → Cloud penetration
	2	Data centers → AI penetration
	3	Data centers → BB penetration
	4	Digital adoption → Productivity
Employment	5	Digital adoption → Employment
Mechanisms	6	Data centers → Digital companies
	7	Data centers → BB infrastructure
Negative externality	8	Data centers → Electricity price
	9	Electricity price → Investment

Source: Telecom Advisory Services analysis

The verification of these causal linkages will make it possible to estimate end-to-end effects, leading from large data center deployment (driver in hypotheses 1–3) to a productivity increase (impact in hypothesis 4). From the end-to-end effects and considering the potential impact of data centers on employment levels (hypothesis 5), the GDP gains will also be estimated.

In a second round of estimates, we will dig further into the mechanisms that take place between data center deployment and digital adoption (hypotheses 6 and 7), although these estimates will not be considered in the simulation of end-to-end effects (hypotheses 1–4) due to the identification problems highlighted above that arise from running the complete model, as outlined in the left side of Figure III-1. Finally, we will also test if cloud zone deployments effectively increase electricity prices and, because of this, whether some investment crowding out might take place (hypotheses 8 and 9).

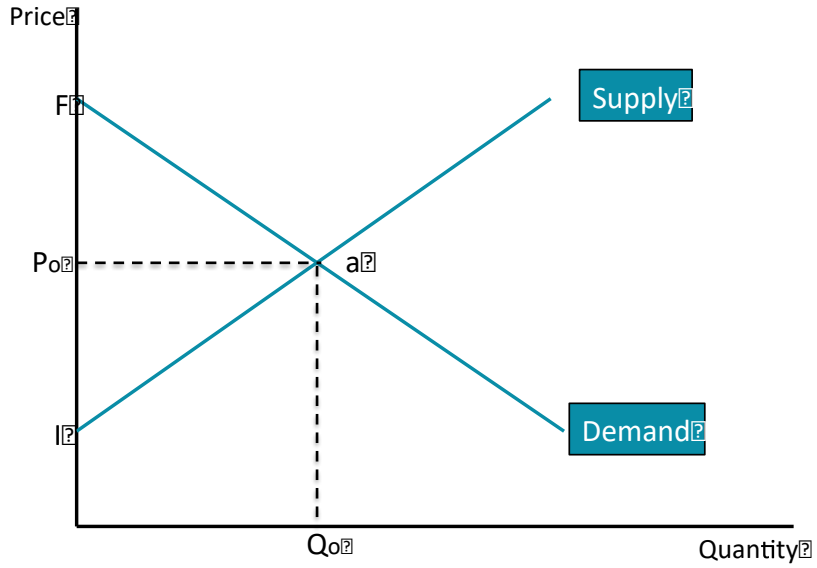
Finally, we will estimate the increase in consumer mobile users triggered by the growth in broadband adoption (hypothesis 3 above), which will yield increased adoption of digital services and, in turn, drive additional consumer surplus.

IV. THEORETICAL FRAMEWORK TO MEASURE CONSUMER SURPLUS DERIVED FROM DATA CENTER DEPLOYMENT

IV.1. Theoretical framework

Prior research[2] establishes that, in addition to the contribution to productivity and GDP, the economic value of digital goods needs to be measured based on the concept of economic surplus. The underlying framework implicit in measuring the economic surplus approach is captured in Figure IV-1.

Figure IV-1. Measurement of economic surplus



The economic surplus is based on the difference between the value of units consumed and produced up to the equilibrium price and quantity, allowing for the estimation of consumer surplus (area of F, Po, a) and producer surplus (area of Po, I, a).[3] Consumer surplus measures the total amount consumers would be willing to pay to have the service compared to what they actually pay, while producer surplus measures the analogous quantity for producers, which is essentially the economic profit they earn from providing the service. In Figure IV-1 the total economic surplus is contained in the area F, I, a.

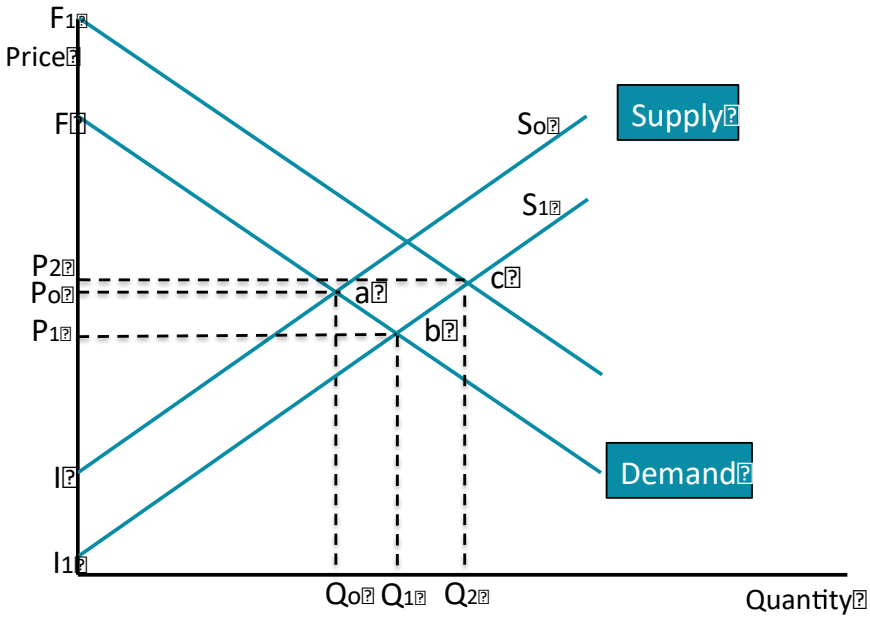
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[2] Thanki, R. (2009). *The economic value generated by current and future allocations of unlicensed spectrum*. London: Perspective Associates; Thanki, R. (2012). *The Economic Significance of License-Exempt Spectrum to the Future of the Internet.* London: Perspective Associates; Milgrom, P., Levin, J., and Eilat, A. (2011). *The case for unlicensed spectrum*. Stanford Institute for Economic Policy Research Discussion Paper No. 10-036.

[3] Following Alston (1990), we acknowledge that this approach ignores effects of changes in other product and factor markets; for example, ultra-wideband also increases the economic value of technologies operating in licensed bands (Alston, J.M. and Wohlgenant, M.K. (1990). "Measuring Research Benefits Using Linear Elasticity Equilibrium Displacement Models". John D. Mullen and Julian M. Alston, *The Returns to Australian Wool Industry from Investment in R&D*, Sydney, Australia: New South Wales Department of Agriculture and Fisheries, Division of Rural and Resource Economics).

Consistent with the concept presented above, the approach to be relied upon in this study to measure consumer value of digital goods whose adoption is stimulated by data center deployment focuses on the surplus generated after their adoption.[4] The underlying assumption is that the adoption of broadband internet, stimulated by data center deployment, generates a shift both in the demand and supply curves resulting from the corresponding willingness to pay for its acquisition. Since the demand curve is derived from the utility function, a greater benefit to the consumer derived from the reliance on digital goods at a stable price will yield an increase in the willingness to pay, and consequently a shift in the demand curve (see Figure IV-2).

Figure IV-2. Measurement of economic surplus resulting from a supply and demand shift



Under these conditions, total economic value is now represented by the area P_1, b, I_1 in Figure IV-2, representing both changes in consumer surplus.

As stated above, consumer surplus represents the area below the demand function for a given good or service and above the price (which, in the case of many digital goods and services, is nil, due to zero marginal costs to produce them). Then, consumer surplus of a digital good can be measured as the willingness to pay for the product that is offered for free (e.g., Google Search), since the value it generates for consumers is available at zero price.[5] Accordingly, assessing the consumer surplus of free products requires measuring their consumers' subjective valuation.[6]

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[4] See a similar approach used by Mensah and Wohlgenant (2010) to estimate the economic surplus of adoption of soybean technology (Mensah, E., and Wohlgenant, M. (2010). "A market impact analysis of Soybean Technology Adoption", *Research in Business and Economics Journal*).

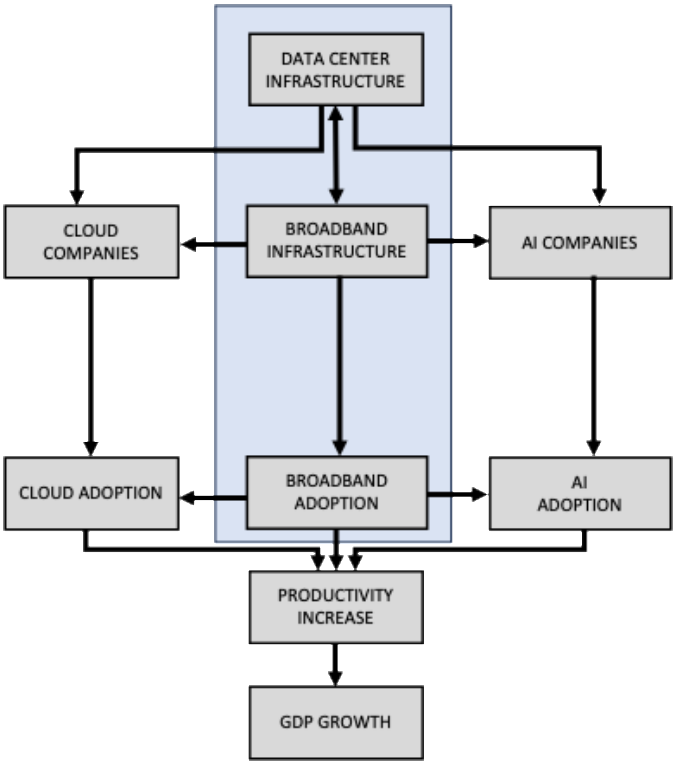
[5] Brynjolfsson, E., & Collis, A. (2019). "How should we measure the digital economy?" *Harvard Business Review*, *97*(6), 140-148.

[6] Wertenbroch, K., & Skiera, B. (2002). "Measuring consumers' willingness to pay at the point of purchase". *Journal of Marketing Research*, *39*(2), 228-241.

IV.2. Methodology for measuring consumer surplus generated by data center deployment

The underlying assumption for estimating the consumer surplus generated by data center deployment is that the latter is stimulating consumption of goods that are offered at zero price to consumers. Accordingly, the consumer surplus would be equivalent to their willingness to pay for adopting such goods. The initial trigger of such calculation is the incremental number of mobile broadband subscribers as estimated in the causal chain used in estimating the impact on productivity and GDP and highlighted in Figure IV-3.

Figure IV-3. Diagram for estimating the incremental number of broadband subscribers



Source: Telecom Advisory Services

According to the causal chain depicted above, the development of broadband infrastructure resulting from data center deployment stimulates broadband adoption. The econometric model predicts adoption as measured by total mobile broadband subscriptions (per 100 people). However, this metric could potentially overestimate the number of subscribers, and consequently the estimation of consumer surplus, due to dual phone usage behavior (for example, enterprise cellphones and consumer cellphones). Therefore, total mobile broadband subscriptions need to be converted to a more precise indicator: unique mobile subscribers. This conversion should eliminate enterprise mobile subscribers, since consumer surplus should be driven exclusively by consumer usage. The conversion is done by relying on the ratio unique mobile subscribers/total mobile subscriptions as calculated for each country by the GSMA. Along these lines, for the purpose of the analysis, we rely on the incremental number of unique mobile subscribers

generated by the development of broadband infrastructure triggered by data center deployment.

The incremental unique mobile subscribers will serve to calculate the consumer surplus generated by the deployment of data centers. For this purpose, we rely on a study developed by Brynjolfsson et al. (2026)[7] where the willingness to accept money (for the average citizen) for giving up the use of a digital platform for a month is estimated based on survey data (the study relies on 39,717 observations from Facebook users for 13 countries: United States, Canada, Mexico, Germany, United Kingdom, Ireland, France, Belgium, Norway, Spain, Romania, Japan, and Korea). The study assumes that the monetary value that an individual is willing to accept for stopping the use of a service is close to the value that the individual assigns to a particular service.[8] Among the relevant platforms, the study provides estimates for Google Search, YouTube, Google Maps, WhatsApp, Facebook, TikTok, Amazon, Instagram, Twitter (X) and Snapchat for each country where the survey was conducted (see Table IV-1).

Table IV-1. Willingness to accept for 10 digital services by country (annual value in US$) (survey conducted in 2022)

	Google Search	YouTube	Google Maps	WhatsApp	Amazon	Facebook	TikTok	Instagram	Twitter (X)	Snapchat
United States	102	62	58	28	55	49	37	26	20	18
Germany	126	55	70	115	54	37	27	31	17	15
Norway	133	73	59	33	39	57	34	41	20	60
France	81	47	41	39	32	36	22	29	15	22
United Kingdom	82	42	46	57	47	33	25	23	16	16
Ireland	93	51	51	75	33	30	27	31	21	27
Canada	87	54	45	27	41	37	26	24	17	19
Spain	59	36	53	81	29	27	22	25	17	11
Mexico	21	18	17	31	11	15	11	11	9	8
South Korea	37	41	12	8	12	16	8	20	8	6
Japan	40	33	26	8	23	17	7	16	15	4
Romania	15	13	10	17	6	11	7	5	4	4
Belgium	72	47	37	45	24	39	22	26	15	18

Source: Brynjolfsson et al. (2026).

However, since not all incremental unique mobile subscribers adopt all digital services, the indicators from Table IV-1 need to be converted to reflect service adoption (in other words, not all mobile broadband subscribers use Instagram). This calculation relies on adoption values for each service by country (as provided by different public sources: Gartner, Statista, Statcounter, etc.).

[7] Brynjolfsson, E., Collis, A., Liaqat, A., Kutzman, D., Garro, H., Deisenroth, D. and Wernerfelt, N. (2026) *The digital welfare of nations: new measures of welfare gains and inequality*. National Bureau of Economic Research (May).

[8] A sample question in the survey is as follows: "Would you be willing to stop using Facebook for one month in exchange for $40?"

While this is probably the only assessment of consumer surplus by country of digital goods, it is still subject to some limitations. As pointed out by the authors of the source study, the data could be relatively noisy. In addition, the values reflect a point in time, recognizing that willingness to accept is subject to diffusion stages and the influence of network effects. Furthermore, extrapolating consumers' stated acceptance from one month to twelve months will increase the WTA estimate, since the one-month value is multiplied by 12 (Brynjolfsson and Collis, 2019). That being said, it is the only research that provides order-of-magnitude differences across platforms and countries. As the study results indicate, WTA of digital goods varies significantly across countries, reflecting in part the context in which digital goods are offered.

More importantly, it should be noted that Willingness to Accept (WTA), as measured by the Brynjolfsson et al. (2026) study we rely on, does not equal Willingness to Pay (WTP), which is the more accurate metric of consumer surplus. Empirical studies generally indicate that WTA is larger than WTP. In other words, empirical work indicates that asking subjects how much they will pay to acquire a good might not yield answers equal to how much they should be paid to forgo that good. As explained by Fisher et al. (1988), "one possible explanation of the disparity is that WTP is constrained by the consumer's budget, while WTA has no similar constraint". For example, Hanemann (1991) explains that, in the case of no substitutes for the product being evaluated, WTA and WTP can vary greatly depending on how close the product is to a substitute and the income of the adopting subject. Under this assumption, Facebook being a close but not complete substitute for Instagram, the WTA values presented by Brynjolfsson et al. (2026) could be overestimated. In addition, Kahneman, Knetsch, and Thaler (1990) show empirically that, even under low-income differentiation, WTA and WTP differ. The difference in this case is the result of what the authors call the "endowment effect": WTA is higher than WTP if the subject has already adopted the good (see Thaler, 1980): in other words, the willingness to give up a good is greater than the utility of acquiring it. Consequently, if we were to take the WTA values from Table IV-1 as estimated by Brynjolfsson et al. (2026) at face value, we would be overestimating consumer surplus. An empirical study by Kahneman, Knetsch, and Thaler (1990) indicates an approximate discount of 50% of WTA to estimate WTP, under conditions of no income differentiation, which is the case under analysis.[9] However, since the digital services we are dealing with are free, it stands to reason that a WTA to WTP discount would not apply in this case. This is because consumers are accessing the digital good for free (for which they believe they have property rights), WTA equals consumer surplus.

[9] As a matter of fact, Fisher et al. (1988) present a compilation of empirical studies where the ratio of WTA to WTP ranges from 2 to over 10.

V. PANEL DATA SAMPLE AND DESCRIPTIVE ANALYSIS

The econometric models to be estimated in the empirical approach presented in Section III depend on several variables that are available for only a subset of countries. We were able to build a panel covering the period 2015-2025 for a sample of 39 countries, belonging to different regions of the world, such as Western and Eastern Europe, North and Latin America, Asia Pacific and the Middle East. In Table V-1 we present the list of countries that were included in the data sets to be used in the econometric models.

Table V-1. Countries included in the sample

Australia	Germany	Netherlands
Austria	Greece	New Zealand
Belgium	Hungary	Norway
Brazil	Iceland	Poland
Bulgaria	Ireland	Portugal
Canada	Israel	Romania
Colombia	Italy	Slovak Republic
Croatia	Japan	Slovenia
Czech Republic	Korea	Spain
Denmark	Latvia	Sweden
Estonia	Lithuania	Turkey
Finland	Luxembourg	United Kingdom
France	Mexico	United States

Source: Telecom Advisory Services analysis

We built a national-level sample for all estimates, and also a sectoral-level sample to provide additional estimates of productivity and employment drivers. The set of variables compiled for the econometric analysis is detailed in Table V-2, along with their descriptions and sources.

Table V-2. Variable definitions

Group	Variable	Description	Source
Data infrastructure	Cloud zones	Cloud region zones (hyperscaler, Edge, GPU)	TeleGeography
	Cloud zones GW	Cloud zones capacity (in GW)	Built from TeleGeography and ABI
Digital adoption (*)	Cloud penetration	Percentage of companies purchasing cloud computing	OECD
	AI penetration	Percentage of companies using AI	OECD
	FBB penetration	Fixed broadband subscriptions (per 100 people)	ITU
	MBB penetration	Mobile broadband subscriptions (per 100 people)	ITU
Macroeconomic indicators	GDP	Gross Domestic Product (million real dollars)	PWT / IMF
	VA	Value added (million real dollars)	OECD
	Capital	Physical capital stock (million real dollars)	PWT / IMF / OECD
	Investment	Investment (% of GDP)	IMF
	Workers	Persons employed (in thousands)	TCB / OECD
	TFP	Total Factor Productivity index (2015=100)	TCB
Instruments	Submarine cables	Quantity of internet submarine cables	Desktop research

Group	Variable	Description	Source
	Capacity of submarine cables	International bandwidth capacity (in million Mbit/s) of countries that receive submarine cables	ITU
	Fixed telephone adoption 1990	Fixed telephone penetration in 1990 (per 100 people)	ITU
	Fixed telephone adoption 1995	Fixed telephone penetration in 1995 (per 100 people)	ITU
Digital ecosystem mechanisms	Cloud companies	Quantity of cloud computing companies per million people	Crunchbase
	AI companies	Quantity of AI companies per million people	Crunchbase
	Big Data companies	Quantity of Big Data companies per million people	Crunchbase
	IoT companies	Quantity of IoT companies per million people	Crunchbase
	Fintech companies	Quantity of Fintech companies per million people	Crunchbase
Broadband mechanisms (*)	FTTH coverage	Households passed by a FTTH network (per 100 households)	FTTH Council / IDATE / FTTH M.P. / FBA / SMC+
	5G coverage	Population covered by at least a 5G network (%)	ITU
	FBB speed	Average downloading speed for fixed broadband (Mbps)	Ookla
	MBB speed	Average downloading speed for mobile broadband (Mbps)	Ookla
Controls (*)	FBB price	Fixed broadband basket (5 GB) in real dollars	ITU
	MBB price	Data-only MBB basket (2 GB) in real dollars	ITU
	Cloud ARPU	Average revenue per company purchasing cloud services (real dollars)	IDC / OECD
	AI ARPU	Average revenue per company using AI (real dollars)	IDC / OECD
	Population	Population (in millions)	IMF
	Population density	Population per square kilometer	World Bank
	FDI	Foreign direct investment net inflows (% GDP)	World Bank
	Interest rate	Monetary policy interest rate (%)	IMF / desk research
	Saving rate	Gross national savings (% GDP)	World Bank
	Industry	Industry (including construction), value added (% of GDP)	World Bank
	Electricity generated	Electricity generated from different sources (TWh)	Ember
	Electricity coverage	Access to electricity (% of Population)	World Bank
	Electricity price	Price of electricity (real USD cents per kWh)	WB / CableCoUK / GPP
	Renewable energy	Share of renewables across energy generated	Ember
	Wages	Average wage per worker	OECD / TCB
	Human Capital	Average years of education for adults aged 25 and older	UNESCO
	Taxation	Tax revenue (% GDP)	World Bank
	Telecom regulation	Regulatory Regime of the ICT Regulatory Tracker	ITU

Note: (*) linear interpolation/extrapolation conducted to fill missing values
Source: Telecom Advisory Services analysis

Two data infrastructure variables were considered. First, we utilized the number of cloud zones located within cloud regions[10], including hyperscaler, edge, and GPU

[10] A cloud zone, as defined by TeleGeography, represents individual physical data centers (or data center sites) operated by cloud service providers. Cloud zones are of three types: 1) hyperscaler zone, 2) an edge zone (also called a local cloud zone), which places compute, storage, database, and other services closer to end-users, allowing customer organizations to run applications that require single-digit millisecond latencies to their end-users. Each Local Zone location is an extension of a Region which is a physical location clustering a group of data centers. 3) A GPU zone is a facility deployed by a neocloud, also considered to be an AI factory. A region is defined as a geographic territory (often a specific metro area) that acts as a collection of one or multiple cloud zones. Zones are connected via high-speed, low-latency network links. For example, the Google Paris (Europe west9) region comprises three zones.

infrastructures, and sourced from TeleGeography.[11] Throughout this report, the term cloud zone is used interchangeably with data center.

In particular, as indicated in Table V-2, an indicator of cloud zone capacity by country (measured in GW) was also constructed. The advantage of using total capacity is that it captures more precisely the input of computing power likely to have an economic effect. The data and approach used to calculate this critical variable were as follows:

- **Data used to estimate cloud capacity**: According to ABI Research, Edge zones have a theoretical capacity of less than 1 MW. Considering this information, we considered 0.5 MW the average capacity for these types of data centers. ABI Research also reports that the theoretical capacity of GPU data centers can reach more than 50 MW, while for hyperscalers it can reach more than 100 MW.[12] However, these capacity values were defined by ABI for the period 2025-2035, meaning that those benchmarks are expected to overestimate real capacities for the period considered in our panel. In addition, the fact that these infrastructures can operate at a certain capacity does not mean that they are actually doing so; they start providing service at lower levels and scale it up when they secure new contracts. This interpretation is reinforced by the fact that ABI Research reports that 13% of European GPUs have a current capacity of less than 10 MW (8% in North America, and 6% of GPUs in Asia Pacific are in the same situation). Similarly, ABI Research reports that 10% of European hyperscalers have a current capacity of less than 10 MW (7% in North America, and 9% of Asian and Latin American hyperscalers are in the same situation).[13] Considering this evidence, it is important to rely on a conservative approach when using these benchmarks to build a capacity proxy.

  For edge zones we assume an average capacity of 0.5 MW, while for the remaining ones, capacity will depend on the share of data centers reported to operate below 10 MW (we assume an average of 5 MW in these cases) while for those operating above 10 MW, we take a conservative value of the midpoint in the interval between 10 MW and the theoretical capacity we assume they can reach (50 MW for GPU and 100 MW for hyperscalers).[14]

- **Calculation of country data center capacity**: The formula to calculate the average capacity by type of data center in region r is the following:

$$Average\ capacity_r \begin{cases} Edge_r^{Cap} = 0.5\ MW \\ GPU_r^{Cap} = [(share < 10)_r^{GPU} * 5 + (share > 10)_r^{GPU} * 30]\ MW \\ Hyperscaler_r^{Cap} = [(share < 10)_r^{H} * 5 + (share > 10)_r^{H} * 55] MW \end{cases}$$

[11] TeleGeography (2026). *Cloud & WAN infrastructure*. Washington, DC: PriMetrica.
[12] ABI Research (2026). *Next Generation Data Centers*. New York.
[13] Gergs, L. (2026). Where is AI data center demand growth being driven? London: ABI Research.
[14] Because capacity is built from conservative average values rather than observed facility-level data, the resulting measurement error and compressed cross-country variation will make harder, not easier, to detect an effect in econometric analysis, so our estimates are more likely to understate than overstate the impact of data center capacity on technology adoption.

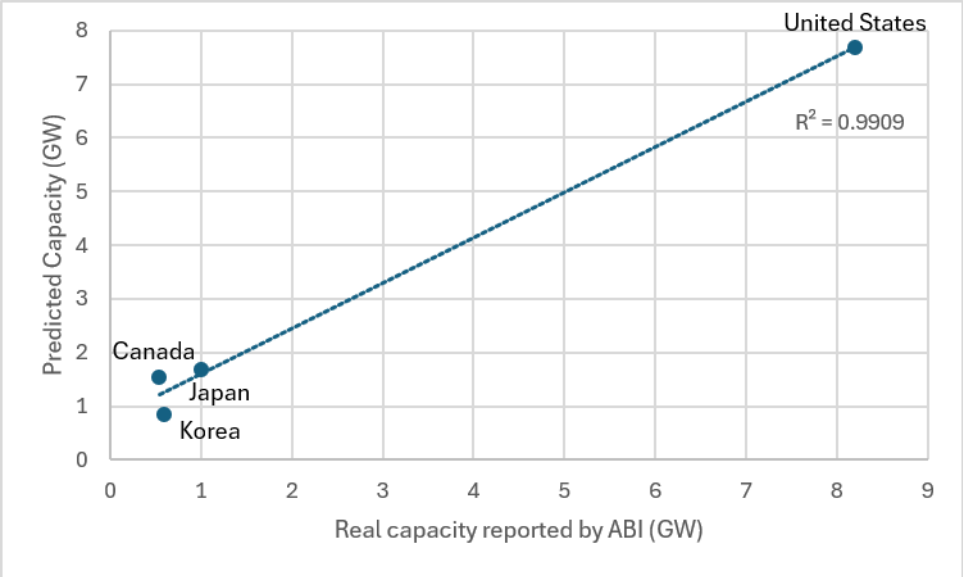
Taking these average capacities as a reference for data centers, we calculate the total cloud zone capacity by country i belonging to region r in year t:

$$Cloud\ zones\ GW_{irt} = \frac{\left(Edge_r^{Cap}\right)*Edge_{it}+\left(GPU_r^{Cap}\right)*GPU_{it}+(Hyperscaler_r^{Cap})*Hyperscaler_{it}}{1000}$$

The division by 1000 is done to convert MW into GW.

- **Calibration of estimates**: once capacity was calculated by country, it was compared against the actual capacities reported for the United States, Canada, Japan and Korea for 2025. This comparison is reported in Graphic V-1.

Graphic V-1. Scatterplot of actual versus predicted cloud zone capacity in 2025



Source: ABI, TeleGeography, Telecom Advisory Services analysis

The comparison of predicted and actual values indicates that the proposed formula for calculating capacity fits fairly well with the actual values (R2 of 0.99), although it slightly underestimates the actual capacity of the United States while it overestimates that of Canada.[15]

Regarding adoption, we used cloud computing and AI enterprise adoption (measured as the percentage of firms with over 10 employees using these technologies, source: OECD Stat), as well as fixed and mobile broadband adoption (subscriptions per 100 people, source: ITU data hub). The data reported by OECD regarding cloud and AI adoption can also be split by size of establishment, which means that we can also rely on OECD adoption by enterprise size category, distinguishing between small and medium-sized enterprises (SMEs) versus large firms. The OECD dataset also distinguishes between sectors of activity, allowing us to conduct sector-level estimations.

[15] Unfortunately, data is not available for countries other than the United States, Canada, Japan and Korea, and even for these, no time-series is available.

As for macroeconomic indicators, our main dependent variables were labor productivity (built as GDP per worker in the national sample, and as value added per worker in the sectoral sample) and total factor productivity (TFP, built as an index taking values of 100 for the first year of our sample, 2015). For the national-level sample, the GDP and the physical capital stock were obtained from the Penn World Table (PWT) up to 2023 and expanded to 2025 relying on IMF data of growth rates and investment, also considering the depreciation rate of capital stock as reported by PWT. The number of employees and TFP growth were compiled from The Conference Board in the case of the national sample. In the case of the sector-specific sample, value added, employment and capital stock were obtained from the OECD Statistical Site. All variables in our model that are expressed in monetary units were deflated into constant prices to avoid distortions generated by inflation (constant prices in 2021 dollars).

We also compiled a set of instruments, as in the adoption regressions, the cloud zone regressors can be endogenous. Similarly, the digital adoption indicators in the productivity equations should be endogenous as well. Therefore, we instrumented cloud zones with submarine cable variables. On the one hand, we built from desktop research a time series of the number of submarine cables by country. On the other hand, we approximated submarine cable capacity by international bandwidth, as reported by the ITU in countries that display submarine cable landings (0 in the case of landlocked countries). Of note, submarine cables require multilateral consortium agreements and years of planning; their activation provides discrete bandwidth shocks exogenous to the contemporaneous domestic business cycle, which renders this series an appropriate instrument.

In addition, legacy-technology indicators of diffusion, with long-term lags, were used as instruments for technology adoption in productivity equations. Fixed telephone penetration levels from decades ago proxy the density of the incumbent copper local-loop network (ducts, cabinets, exchanges) that operators subsequently reused and upgraded to deploy DSL/fiber broadband. Areas with a denser legacy telephone network therefore should experience faster and more extensive broadband-infrastructure rollout, giving the instrument strong predictive power for endogenous regressors associated with broadband or technology adoption. As the stock of fixed telephone lines was shaped several years ago by universal-service obligations, population density and voice-demand conditions that predate the current technologies, these technologically obsolete networks should not have any direct effect on present-day outcomes; the long lag also precludes reverse causality. Specifically, the instruments used were the adoption levels of a legacy technology (fixed telephony) with long-enough lags (values for 1990 and 1995), interacted with a time trend. Therefore, these instruments consist of static historical variables, interacted with a time trend. This avoids identification based on historical year-over-year growth rates of telephone penetration, as is the case with time-varying variables under panel settings.

Finally, for assessing the impact of cloud zone deployment on digital innovation, we considered the creation of digital companies (offering cloud, AI, Big Data, IoT and Fintech services, in all cases the data source is Crunchbase), as well as some metrics

related to broadband infrastructure: FTTH coverage (compiled from very different data sources such as FTTH Council, IDATE, FTTH/B Market Panorama, Fiber Broadband Association, and SMC+), 5G coverage (from ITU data hub), as well as average broadband speeds (from Ookla Speedtest).

Some of the outcome groups (digital adoption variables) and some controls were incomplete within the 2015–2025 timeframe. In these situations, missing values were filled through linear interpolation and extrapolation. Even at this point, not all variables were available for all 39 countries, meaning that the estimates will vary in the number of observations. The national-level econometric estimation to be conducted with the largest number of countries includes 39, while the one to be conducted with the smallest set consists of 17. In the case of the sectoral ones, the estimate conducted with the largest number of countries is 29, while the one with the smallest set consists of 10.

In Table V-3 we report the descriptive statistics for the main groups of variables of the panel, including the mean and standard deviation. The average number of cloud zones across the sample is 8.24. As for adoption levels, average broadband adoption in the sample reaches values of 33.35 (fixed broadband) and 108.89 (mobile broadband) connections for every 100 people. In turn, on average 39.54% of firms were cloud adopters, while only 10.36% had adopted AI. However, if we consider only the last year (2025), a total of 19.43 out of every 100 firms were using AI, which indicates the rapid evolution in adoption levels of this technology.

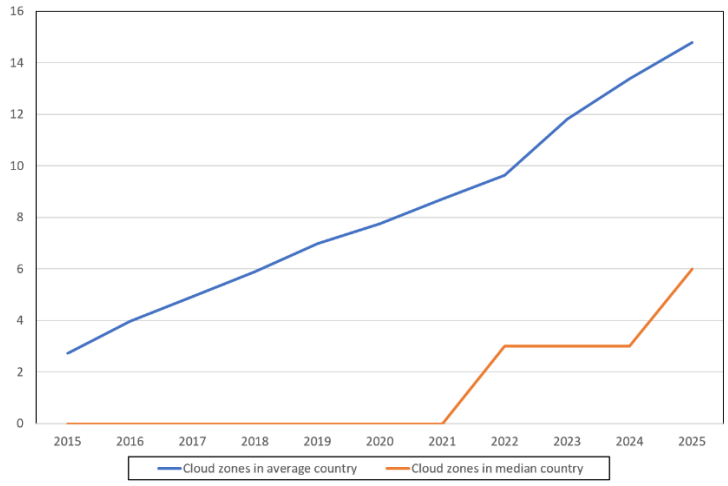
Table V-3. Main descriptive statistics

Group	Variable	Country-level sample		Sector-level sample	
		Mean	Std. Dev.	Mean	Std. Dev.
Data infrastructure	Cloud zones	8.235	20.573		
	Cloud zones GW	0.365	0.884		
Digital adoption	Cloud penetration	39.538	20.634	41.763	24.907
	AI penetration	10.361	8.002	10.576	13.006
	FBB penetration	33.351	8.296		
	MBB penetration	108.887	33.731		
Macroeconomic indicators	GDP	1,822,691	3,766,101		
	VA			108,796	256,719
	Capital	7,915,132	13,300,000	414,287	1,487,509
	Investment	22.945	4.211		
	Workers	18,879	30,363	0.951	1.845
	TFP	101.226	4.201		

Source: Telecom Advisory Services analysis

The deployment of cloud zones has been progressively increasing throughout the period; if we consider the last year of data available (2025), there were already 14.79 zones on average (Graphic V-2).

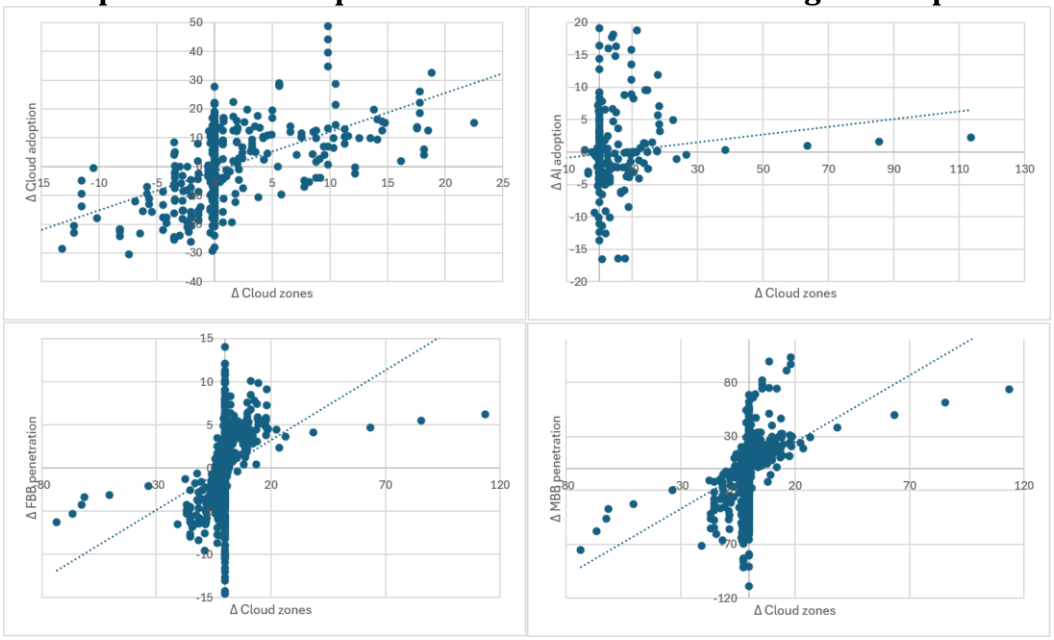
Graphic V-2. Average and median cloud zones by country



Source: TeleGeography, Telecom Advisory Services analysis

Preliminary evidence suggests that the deployment of cloud zones is positively related to the adoption of digital technology, as depicted in Graphic V-3 (data points presented consist of deviations with respect to each country's mean). The positive association seems to be more pronounced in the case of cloud, fixed and mobile broadband, while slightly less in the case of AI.

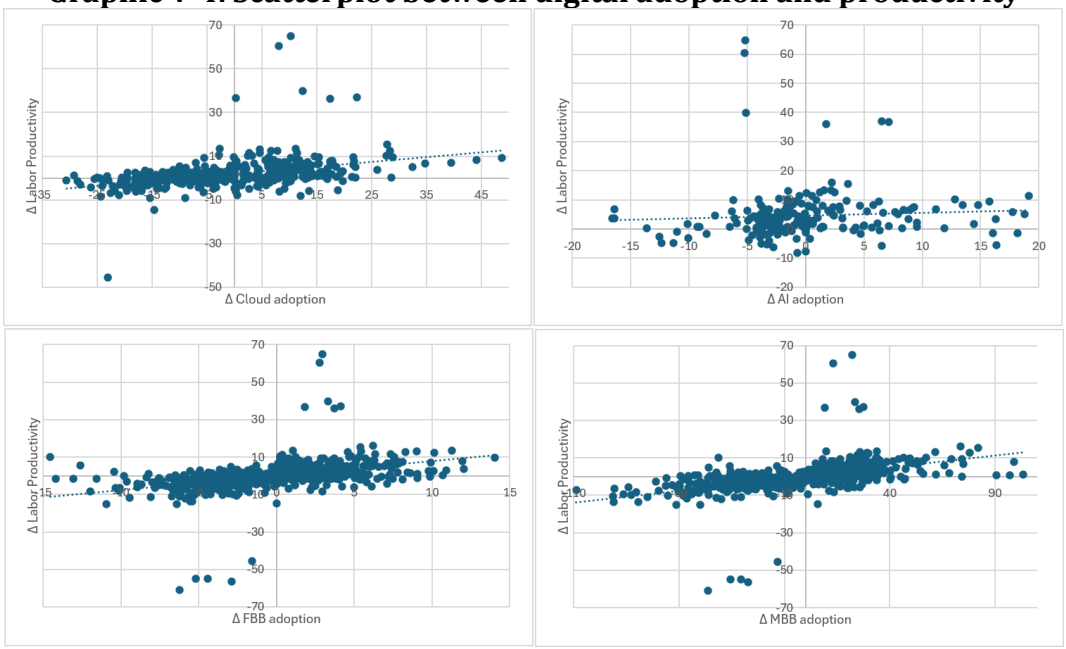
Graphic V-3. Scatterplot between cloud zones and digital adoption



Source: Telecom Advisory Services analysis

Finally, Graphic V-4 presents the link between digital adoption indicators and labor productivity (GDP per worker). Again, the positive association seems to be more pronounced in the case of cloud, fixed and mobile broadband, while slightly less in the case of AI, possibly because adoption is still in its early days for this technology.

Graphic V-4. Scatterplot between digital adoption and productivity

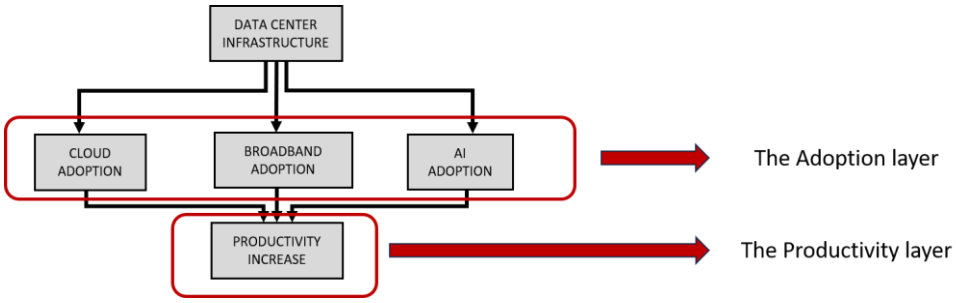


Source: Telecom Advisory Services analysis

VI. ECONOMETRIC MODEL RESULTS

Having reviewed the indicators used in the modeling exercise, we now report the results of the econometric analysis. As discussed in Section III, the econometric models will be estimated following the steps in the reduced-form model presented in Figure VI-1: first, an adoption layer (measuring the impact of data center deployment on digital adoption), and second, the productivity layer, addressing how the adoption of technology influences productivity gains.

Figure VI-1. Reduced-form model specification



Source: Telecom Advisory Services analysis

After the estimation of the reduced-form model for estimating productivity effects, we address the impact on employment and explore the potential mechanisms that may explain why data center deployment should influence technology adoption as suggested through the adoption layer. We also conduct further estimates to address potential negative externalities from data centers through crowding-out effects on other investments.

VI.1. The adoption layer

The adoption layer models were estimated for four technologies: cloud computing, AI, fixed and mobile broadband.

We begin the analysis of the impact of data center infrastructure on cloud computing adoption. All estimates are conducted with country and year fixed effects and robust standard errors that are heteroscedasticity consistent, allowing for autocorrelation up to lag two, while being robust to cross-country spatial dependence (Driscoll and Kraay, 1998). The empirical specification to be estimated is presented as follows:

$$Log(Cloud\ adoption_{it}) = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where i and t denote country and year. In addition, α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as cloud ARPU (introduced to proxy price levels), income per firm (in lags), human capital, and broadband speeds.

The first estimate presented in column (1) of Table VI-1 introduces the number of cloud zones as drivers of cloud adoption. This estimate is conducted through Ordinary Least Squares (OLS), with results suggesting a positive effect from cloud zones on cloud adoption (coefficient of 0.0046, significant at the 1% level). This result can be interpreted as follows: the deployment of a new cloud zone increases cloud enterprise adoption by 0.5% after one year (as the regressor is introduced in lags). Among the controls, cloud ARPU exhibits an expected negative sign, as higher prices reduce demand. Income levels, in turn, present a positive and significant coefficient, as expected from any normal good or service.

We also introduce controls for broadband speeds and for human capital, allowing them to yield a specific effect depending on the level of development of the country (by introducing their interaction with a dummy variable that identifies those countries with income per capita below the median of the sample). Fixed broadband speeds seem to be a relevant driver of cloud adoption in the less developed countries of the sample, but not in the richer ones. Mobile broadband speeds exhibit an insignificant effect in lower-income countries of the sample, while the coefficient for those with the largest incomes per capita is negative. Something similar happens in the case of human capital, which in both cases reaches negative coefficients. This does not mean higher human capital or mobile broadband speeds trigger reductions in cloud adoption. We believe this to be a normal situation *within* models such as fixed effects panels, where countries with a faster pace of increase in broadband speeds or years of education (usually those that are lagging behind) are usually slower in adopting novel technologies such as cloud and AI.

The inclusion of cloud ARPU (Average Revenue per User) as a regressor, even if necessary to control for price variations, can raise some endogeneity concerns. First, prices are the result of market forces of supply and demand, therefore influencing adoption levels. Second, ARPU depends on the number of users. Therefore, we replicate the estimate presented in column (1) but omitting this regressor, in column (2). Results indicate that removing the ARPU control contributes to increasing the

coefficient linking cloud zones with cloud adoption, meaning that any potential bias generated by using this control will be downward, yielding more conservative results. This will be verified again when conducting estimates using the cloud zone capacity indicator. In addition, when conducting estimates using IV, we will also check if the results are affected when considering cloud ARPU as an endogenous regressor.

In column (3) we replicate the estimate of column (1), but now relying on the cloud zone capacity indicator in GW, rather than on the quantity of zones. Results again verify that the higher the capacity of cloud zones, the larger cloud adoption becomes (coefficient of 0.0989, significant at the 1% level). The effect can be quantified as follows: an increase of 1 MW (0.001 GW) of zone capacity is associated with a 0.010% increase in cloud adoption in the following year. In column (4) the estimate is repeated, but now omitting the cloud ARPU regressor, with results again pointing to an increase in the coefficient linking cloud zone capacity and adoption. This confirms that using the ARPU regressor should not be a concern under our specification.

Table VI-1. Drivers of cloud adoption

Dep. variable: Log(Cloud adoption)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Country sample	All	All	All	All	All	Excluding landlocked	All	All	Excluding landlocked	All
Cloud Zones t-1	0.0046***	0.0070***			0.0063***	0.0080***	0.0083**			
	[0.0011]	[0.0016]			[0.0023]	[0.0025]	[0.0036]			
Cloud Zones GW t-1			0.0989***	0.1714***				0.1575**	0.1517*	0.2414*
			[0.0282]	[0.0363]				[0.0748]	[0.0894]	[0.1292]
Log(Cloud ARPU)	-0.4402***		-0.4390***		-0.4647***	-0.4658***	-0.7472***	-0.4615***	-0.4633***	-0.7501***
	[0.0707]		[0.0707]		[0.0723]	[0.0760]	[0.1241]	[0.0704]	[0.0740]	[0.1296]
Log(Income per firm) t-1	0.3887***	0.0939*	0.3879***	0.0958*	0.4127***	0.3713***	0.6449***	0.4149***	0.3676***	0.6594***
	[0.0914]	[0.0486]	[0.0913]	[0.0493]	[0.1339]	[0.1315]	[0.1303]	[0.1355]	[0.1349]	[0.1383]
Log(FBB speed)	-0.0480	0.0349	-0.0478	0.0337	0.1089**	-0.0083	0.0849	0.1066**	-0.0001	0.0750
	[0.0553]	[0.0642]	[0.0554]	[0.0636]	[0.0519]	[0.0470]	[0.0521]	[0.0501]	[0.0378]	[0.0572]
Log(FBB speed) x Income < median	0.0636*	-0.0191	0.0638*	-0.0193	-0.0481	0.0685	-0.0271	-0.0502	0.0609	-0.0270
	[0.0301]	[0.0475]	[0.0297]	[0.0476]	[0.0856]	[0.1253]	[0.1122]	[0.0848]	[0.1229]	[0.1111]
Log(MBB speed)	-0.1641**	-0.4131***	-0.1636**	-0.4188***	-0.1502***	-0.0764**	-0.0225	-0.1567***	-0.0798**	-0.0334
	[0.0527]	[0.0539]	[0.0536]	[0.0545]	[0.0351]	[0.0324]	[0.0777]	[0.0416]	[0.0386]	[0.0797]
Log(MBB speed) x Income < median	0.1545**	0.3177***	0.1531**	0.3203***	0.1452***	0.1045**	0.0646	0.1484***	0.1074**	0.0697
	[0.0527]	[0.0589]	[0.0532]	[0.0597]	[0.0507]	[0.0450]	[0.0894]	[0.0533]	[0.0490]	[0.0902]
Human Capital	-0.0177***	-0.0159**	-0.0173**	-0.0161**	-0.0101*	0.2144**	-0.0005	-0.0099	0.2257**	-0.0012
	[0.0054]	[0.0059]	[0.0055]	[0.0057]	[0.0058]	[0.1005]	[0.0116]	[0.0061]	[0.0932]	[0.0117]
Human Capital x Income < median	-0.1254**	-0.1839***	-0.1261**	-0.1864***	-0.0639	-0.2802*	-0.0503	-0.0663	-0.2902*	-0.0547
	[0.0412]	[0.0484]	[0.0415]	[0.0485]	[0.0588]	[0.1596]	[0.0552]	[0.0580]	[0.1513]	[0.0531]
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Endogenous regressors					Cloud Zones	Cloud Zones	Cloud Zones and ARPU	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW and ARPU
F-test first stage Cloud Zones t-1					94.85***	95.28***	1946.03***			
F-test first stage Cloud Zones GW t-1								384.18***	86.77***	1723.97***
F-test first stage Log(Cloud ARPU)							308.18***			308.18***
Kleibergen-Paap Wald F-stat					94.853	95.278	329.737	384.184	86.766	517.084
Hansen J stat p-value					0.2292	0.2302	0.2352	0.2257	0.2226	0.2348
Observations	316	316	316	316	231	199	231	231	199	231
R-squared (within)	0.9030	0.8465	0.9029	0.8469	0.8852	0.8734	0.8476	0.8845	0.8728	0.8428
Degrees of freedom	49	48	49	48	45	41	45	45	41	45
RMSE	0.1230	0.1544	0.1230	0.1542	0.0886	0.0906	0.1020	0.0889	0.0908	0.1036
Method	OLS	OLS	OLS	OLS	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

The procedure to estimate the proposed causal effects requires controlling for endogeneity associated with the cloud zones regressor. Endogeneity can arise from reverse causality (where cloud adoption may in turn drive the deployment of cloud zones) or from omitted variables that may be related to both dependent and independent variables. Already under the OLS specification, the inclusion of fixed effects (controlling for all time-invariant heterogeneities) and the introduction of the cloud zones regressors in lags should contribute to alleviating, at least partially, some of these concerns. Still, the appropriate procedure to be confident regarding the causal effects from cloud zones on cloud adoption requires us to conduct estimations using the instrumental variable (IV) methodology.[16] For that purpose, we selected a set of variables to instrument the cloud zone regressor, which may be endogenous.

We will instrument cloud zones with submarine cable variables, such as the quantity of cables and a proxy of their capacity. Submarine cables should be an important driver of cloud zones, as their presence and capacity increase the attractiveness of locations for the deployment of these infrastructures that depend crucially on international connectivity. On the other hand, the exclusion restriction should be verified, as the building of submarine cables requires multilateral consortium agreements and years of planning. We will also introduce them with additional two-year lags with respect to the cloud zone regressor to ensure they are not contaminated with any contemporaneous shocks. It is important to consider that submarine cable capacity provides direct international bandwidth capacity to ISPs, which could in turn lead to cloud adoption, even absent local cloud zones. This means that controlling for broadband speeds is especially critical when using these instruments. Taking all of this into account, these instruments should provide discrete bandwidth shocks exogenous to contemporaneous domestic business cycles.

First-stage estimates (reported in Table A-1 in the Appendix) confirm that both the quantity and the capacity of submarine cables are critical drivers of cloud zones (both in quantity and in capacity), although the effect is heterogeneous by country group: for lower-income countries, the quantity of cables is more relevant than their capacity to explain cloud zone deployments, while for higher-income countries, it is their capacity that matters most.[17] Therefore, the instruments will be used by

[16] We use the IV estimation approach of Limited Information Maximum Likelihood (IV-LIML).

[17] This can be explained as redundancy being a threshold condition, while capacity itself should be more closely related to scaling conditions. In markets with thin submarine cable connectivity (typically lower-income countries), a single cable cut can largely affect a country's entire international bandwidth. Capacity, by contrast, is less relevant at this stage: it doesn't matter how much bandwidth a single cable carries if a backhoe or an anchor can take the whole country offline. This explains why for lower-income countries, quantity acts as a necessary condition while capacity is a second-order concern. However, once redundancy is already secured (as in higher-income economies), capacity dominates. These economies also tend to have larger, more data-intensive digital sectors, which raises the throughput a data center must support. Here, the economically relevant variable becomes total available bandwidth (broadband capacity), because it directly determines whether the market can support the intensive data flows a cloud zone generates — an intensive-margin decision.

allowing their effect to vary by country group, as depicted in columns (2) and (4) in the first stages reported in Table A-1 in the Appendix. Diagnostic tests presented in Table VI-1 confirm that the instruments are strong, while on the other hand the Hansen test does not reject the null hypothesis of their exogeneity.

Results for IV estimates are reported in columns (5) to (10) of Table VI-1, with coefficients confirming the positive causal effect from cloud zone quantities and capacity on cloud adoption. Results presented in column (5) present a coefficient for cloud zones that lies within the intervals of the corresponding estimates conducted under OLS. The coefficient reported in column (5) is not statistically different from that of the OLS estimation in column (1).

In column (6) we replicate the estimation of column (5) but now excluding landlocked countries.[18] The rationale for doing so is that our instruments are accurate for countries that can potentially receive submarine cables, but landlocked countries are not capable of reaching this source of international connectivity for geographic reasons. Results do not change significantly when removing landlocked countries. In turn, in column (7) we also treat cloud ARPU as endogenous, instrumenting it with its own lag. The coefficient linking cloud zones with cloud adoption increases further, confirming that our original solution of including the regressor and treating it as exogenous is actually a conservative approach to assessing the magnitude of the effect of interest.

In columns (8) to (10) we mirror the previous approaches, now for the case of cloud zone capacity. Results confirm the expected effect, and the main conclusions from the previous paragraph are confirmed. All in all, under our preferred specifications, we can interpret the results as every new cloud zone increasing cloud adoption by 0.6% after one year, while the increase of 1 MW of capacity is associated with a 0.016% increase in cloud adoption in the following year. In both cases, we take as the reference the lower bound across the different IV estimates.

In Table VI-2 we explore heterogeneities by firm size. The idea is to verify whether the role of cloud zones in stimulating cloud adoption takes place in SMEs and in big firms. All estimates are conducted through IV. Results reported in Table VI-2 are clear that the main effect verified before regarding the impact of cloud zones on cloud adoption is being driven principally by SMEs, as only for this group of companies does the coefficient of interest reach a statistically significant value. This is verified both for cloud zone quantity and capacity.

Cloud zone deployment operates through the reduction of fixed adoption costs and connectivity-related frictions—latency, data residency compliance, local support, and reliability risk—that represent a proportionally larger barrier for SMEs than for large firms. For SMEs, these costs are a substantial share of the expected value of cloud adoption, so local infrastructure can shift the adoption decision at the extensive margin, consistent with the significant and economically meaningful coefficients found for this group in Table VI-2. Large firms, by contrast, can already replicate the benefits of a local cloud zone through alternative channels—private

[18] Landlocked countries in our sample are Austria, Luxembourg, the Czech Republic, and Hungary.

interconnection and dedicated leased lines, in-house legal and technical capacity to manage compliance even with offshore hosting, multi-region architectures, and bargaining power to negotiate custom SLAs—making physical proximity to a cloud zone a non-binding constraint for their adoption decisions. Additionally, SMEs tend to be more risk-averse toward new technology adoption given their limited capacity to absorb the costs of a failed migration, so the presence of a well-known hyperscale provider locally serves as a credible signal that reduces the information and trust barriers that disproportionately deter smaller firms.

Table VI-2. Drivers of cloud adoption – by firm size

	SMEs		Big firms	
Dep. variable: Log(Cloud adoption)	(1)	(2)	(3)	(4)
Cloud Zones t-1	0.0065***		0.0007	
	[0.0024]		[0.0021]	
Cloud Zones GW t-1		0.1611**		0.0115
		[0.0774]		[0.0595]
Log(Cloud ARPU)	-0.4815***	-0.4782***	-0.2170***	-0.2168***
	[0.0749]	[0.0729]	[0.0291]	[0.0290]
Log(Income per firm) t-1	0.4296***	0.4317***	0.1575***	0.1569***
	[0.1399]	[0.1417]	[0.0366]	[0.0375]
Log(FBB speed)	0.1171**	0.1148**	0.0301	0.0309*
	[0.0532]	[0.0513]	[0.0197]	[0.0179]
Log(FBB speed) x Income < median	-0.0488	-0.0509	0.0326	0.0320
	[0.0882]	[0.0874]	[0.0598]	[0.0605]
Log(MBB speed)	-0.1474***	-0.1539***	-0.1310***	-0.1306***
	[0.0361]	[0.0427]	[0.0287]	[0.0314]
Log(MBB speed) x Income < median	0.1440***	0.1471***	0.1020***	0.1017***
	[0.0532]	[0.0559]	[0.0295]	[0.0306]
Human Capital	-0.0133**	-0.0131**	0.0126***	0.0129***
	[0.0062]	[0.0065]	[0.0045]	[0.0046]
Human Capital x Income < median	-0.0659	-0.0682	-0.0866**	-0.0866**
	[0.0606]	[0.0600]	[0.0357]	[0.0350]
Country Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones GW	Cloud Zones	Cloud Zones GW
F-test first stage Cloud Zones t-1	94.85***		94.85***	
F-test first stage Cloud Zones GW t-1		384.18***		384.18***
Kleibergen-Paap Wald F-stat	94.853	384.184	94.853	384.184
Hansen J stat p-value	0.2293	0.2252	0.3690	0.3738
Observations	231	231	231	231
R-squared (within)	0.8821	0.8814	0.8867	0.8867
Degrees of freedom	45	45	45	45
RMSE	0.0916	0.0918	0.0577	0.0577
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Given that SMEs represent the vast majority of firms in the economies studied,[19] this heterogeneity suggests that the aggregate impact of cloud infrastructure investment operates primarily through the digitalization of the long tail of smaller enterprises, reinforcing the role of cloud zone deployment as a broad-based digital inclusion

[19] On average, SMEs represent more than 97% of the firms with more than 10 employees in the countries in our sample.

mechanism rather than one that principally benefits already-digitalized large incumbents.

Next, we turn to the results for AI adoption, reported in Table VI-3. The empirical specification to be estimated is presented as follows:

$$Log(AI\ adoption_{it}) = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as AI ARPU (introduced to proxy price levels), income per firm (in lags), human capital, and broadband speeds. Estimates for AI are conducted directly through IV, relying on the same set of instruments as in the case of cloud adoption models. Baseline estimates for the complete sample of countries reported in columns (1) and (2) of Table VI-3 show that the effect of cloud zones, measured either in terms of the total number or their capacity equivalent, on AI adoption is not statistically significant.

When excluding the top third of the sample with the higher income per capita, results presented in columns (3) to (8) verify that the role of cloud zones becomes more relevant to explain AI adoption. However, this effect is mostly associated with cloud zone capacity, not with cloud zone quantity (in this latter case, a significant effect at 10% only arises when excluding landlocked countries). As in the case of cloud adoption, models behave similarly when excluding landlocked countries, and when treating AI ARPU as endogenous as well.

AI adoption imposes substantially higher computational and data-throughput requirements than standard cloud services, since training and running AI models involves intensive data transfer, GPU-based processing, and sustained high-bandwidth demands rather than simple storage or application hosting. This can explain why the mere presence of a cloud zone—captured by the quantity variable—is insufficient to drive AI adoption: what matters the most is whether the local infrastructure has the scale to support these compute- and data-intensive workloads, which is precisely what cloud zone capacity measures. In the full sample, this effect is muted because high-income countries—which already possess complementary assets such as skilled AI talent, private high-capacity interconnection, and financial resources to access AI infrastructure abroad regardless of local capacity—are not capacity-constrained in the same way, so their inclusion dilutes the average relationship. Once these countries are excluded, the remaining sample is composed of economies where local cloud capacity is genuinely a binding constraint on the ability to run AI workloads, and it is in this context that cloud zone capacity emerges as a significant driver of AI adoption: firms in these markets need not just access to a nearby cloud zone, but sufficient processing and bandwidth capacity to make AI applications technically and economically viable.

Table VI-3. Drivers of AI adoption

Dep. variable: Log(AI adoption)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country sample	All	All	Excluding income > 66p	Excluding income > 66p & landlocked	Excluding income > 66p	Excluding income > 66p	Excluding income > 66p & landlocked	Excluding income > 66p
Cloud Zones t-1	0.0139		0.0449	0.0508*	0.0415			
	[0.0360]		[0.0300]	[0.0307]	[0.0311]			
Cloud Zones GW t-1		0.5927				1.6206**	1.7162**	1.4974*
		[1.1672]				[0.6833]	[0.6745]	[0.7750]
Log(AI ARPU)	-0.3240***	-0.3339***	-0.2856***	-0.3211***	-0.4617***	-0.3093***	-0.3398***	-0.3604**
	[0.0947]	[0.1167]	[0.0833]	[0.0906]	[0.1524]	[0.1070]	[0.1134]	[0.1618]
Log(Income per firm) t-1	0.3274	0.3882	0.5019	0.4579	0.4079	0.5351	0.4950	0.5063
	[0.3008]	[0.3838]	[0.3966]	[0.4533]	[0.3845]	[0.4600]	[0.5277]	[0.4419]
Log(FBB speed)	0.0957	0.0382	-0.0465	0.0531	0.1990	-0.1535	-0.0487	-0.0601
	[0.1824]	[0.1808]	[0.1694]	[0.2044]	[0.1682]	[0.2038]	[0.2366]	[0.1872]
Log(FBB speed) x Income < median	-0.0607	-0.0026						
	[0.1347]	[0.1644]						
Log(MBB speed)	-0.2048**	-0.2344***	-0.2989**	-0.2974**	-0.2904**	-0.3669**	-0.3614**	-0.3551***
	[0.0862]	[0.0711]	[0.1322]	[0.1414]	[0.1243]	[0.1268]	[0.1535]	[0.1360]
Log(MBB speed) x Income < median	-0.0190	-0.0216						
	[0.0930]	[0.0827]						
Human Capital	-0.0702	-0.0756	-0.5447***	-0.5570***	-0 .5148***	-0.6457***	-0.6575***	-0.6245***
	[0.0734]	[0.0754]	[0.1002]	[0.1129]	[0. 0872]	[0.1254]	[0.1379]	[0.1039]
Human Capital x Income < median	-0.2829***	-0.3353***						
	[0.1079]	[0.1235]						
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones GW	Cloud Zones	Cloud Zones	Cloud Zones and ARPU	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW and ARPU
F-test first stage Cloud Zones t-1	649.86***		82.29***	69.34***	63.16***			
F-test first stage Cloud Zones GW t-1		2236.22***				608.00***	344.26***	168.83***
F-test first stage Log(AI ARPU)					5.79**			5.79**
Kleibergen-Paap F-stat	649.862	2236.217	82.294	69.335	4.706	608.000	344.257	3.871
Hansen J stat p-value	0.3708	0.3488	0.1540	0.1724	0.1112	0.2715	0.3304	0.1953
Observations	174	174	113	101	112	113	101	112
R-squared (within)	0.7339	0.7263	0.6715	0.6287	0.6663	0.6229	0.5751	0.6302
Degrees of freedom	44	44	31	29	30	31	29	30
RMSE	0.2873	0.2914	0.3037	0.3227	0.3059	0.3254	0.3452	0.3220
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Countries excluded in columns (3) to (8) are those from 66p onwards of income per capita distribution in the first year of sample (2015).
Source: Telecom Advisory Services analysis

Taking as a reference the result of the estimate presented in Column (6) of Table VI-3, we can quantify the impact as follows: an increase of 1 MW of cloud zone capacity is associated with a rise in AI adoption of 0.16%. All in all, these results indicate that, when simulating impact for specific countries, the effect of cloud zones on AI adoption will only be considered for the set of countries in our sample that are not part of the top third in income per capita, while the effect will only be related to capacity increases.

As in the case of cloud adoption, results presented in Table VI-4 by firm size verify that the significant effects are driven by SMEs rather than by big companies. As explained above, the capacity barriers reduced by cloud zones represent a proportionally larger challenge for SMEs than for large firms. This means that for the smaller firms, local cloud infrastructure can play a much larger role than for bigger companies in shifting the adoption decision.

Table VI-4. Drivers of AI adoption (exc. income > 66p) – by firm size

	SMEs	Big firms
Dep. variable: Log(AI adoption)	(1)	(2)
Cloud Zones GW t-1	1.7227**	0.4016
	[0.7414]	[0.3462]
Log(AI ARPU)	-0.3226***	-0.2482***
	[0.1160]	[0.0387]
Log(Income per firm) t-1	0.5249	0.3174
	[0.4719]	[0.2969]
Log(FBB speed)	-0.1474	0.4410**
	[0.2825]	[0.2064]
Log(MBB speed)	-0.4021**	0.0094
	[0.1608]	[0.1213]
Human Capital	-0.7392***	-0.1382***
	[0.0899]	[0.0505]
Country Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Endogenous regressors	Cloud Zones GW	Cloud Zones GW
F-test first stage Cloud Zones GW t-1	134.40***	47.75***
Kleibergen-Paap F-stat	134.402	47.752
Hansen J stat p-value	0.2768	0.2535
Observations	112	113
R-squared (within)	0.6023	0.8150
Degrees of freedom	31	31
RMSE	0.3475	0.1856
Method	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998). Countries excluded are those from 66p onwards of income per capita distribution in the first year of sample (2015). Source: Telecom Advisory Services analysis*

Next, in Table VI-5 we present the results for fixed broadband adoption, following a similar empirical strategy as before: conducting estimates through IV, treating cloud zone regressors as endogenous, while also testing results when excluding landlocked countries and treating broadband price as endogenous (instrumenting it with its own lag). Instruments for cloud zone regressors are the quantity and capacity of submarine cables, with a further two-year lag with respect to cloud zones.

The empirical specification to be estimated is presented as follows:

$$Log(FBB\ adoption_{it}) = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as fixed broadband price, GDP per capita (in lags), and fixed broadband speed.

Results presented in Table VI-5 are robust in verifying that both cloud zone quantity and capacity are relevant drivers of fixed broadband penetration, regardless of the specification selected. Results indicate that a new cloud zone deployed increases fixed broadband penetration by 0.17%, while a 1 MW increase in cloud zone capacity is associated with a 0.005% increase in fixed broadband penetration.

Table VI-5. Drivers of fixed broadband adoption

Dep. variable: Log(FBB adoption)	(1)	(2)	(3)	(4)	(5)	(6)
Country sample	All	Excluding landlocked	All	All	Excluding landlocked	All
Cloud Zones t-1	0.0017***	0.0018***	0.0017***			
	[0.0004]	[0.0003]	[0.0004]			
Cloud Zones GW t-1				0.0486***	0.0531***	0.0481***
				[0.0068]	[0.0036]	[0.0068]
Log(FBB price)	-0.0111*	-0.0105**	-0.0068	-0.0130**	-0.0127***	-0.0093
	[0.0063]	[0.0049]	[0.0092]	[0.0062]	[0.0048]	[0.0092]
Log(GDPpc) t-1	0.2169***	0.2144**	0.2225***	0.2198***	0.2196**	0.2246***
	[0.0743]	[0.0968]	[0.0788]	[0.0747]	[0.0989]	[0.0791]
Log(FBB speed)	0.1071***	0.1157***	0.1066***	0.1064***	0.1149***	0.1060***
	[0.0125]	[0.0135]	[0.0128]	[0.0126]	[0.0137]	[0.0129]
Country Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones	Cloud Zones and FBB price	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW and FBB price
F-test first stage Cloud Zones t-1	126.40***	117.74***	1476.04***			
F-test first stage Cloud Zones GW t-1				9714.10***	11000.00***	5395.99***
F-test first stage Log(FBB price)			13.21***			13.21***
Kleibergen-Paap F-stat	126.401	117.736	9.525	9714.104	11000.000	9.317
Hansen J stat p-value	0.4957	0.6395	0.4607	0.4264	0.5649	0.4057
Observations	312	280	312	312	280	312
R-squared (within)	0.6102	0.6052	0.6102	0.6124	0.6075	0.6124
Degrees of freedom	50	46	50	50	46	50
RMSE	0.0483	0.0497	0.0483	0.0481	0.0495	0.0481
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998). Source: Telecom Advisory Services analysis*

Cloud zone deployment stimulates fixed broadband penetration through both demand-side and supply-side channels that reinforce one another. On the demand side, the presence of local cloud infrastructure generates a wider array of data-intensive, latency-sensitive digital services—video streaming, cloud gaming, remote work applications, e-commerce platforms, and enterprise SaaS tools—that are only fully usable over a stable, high-capacity fixed connection, thereby raising households' and firms' willingness to pay for broadband subscriptions. On the

supply side, a nearby cloud zone acts as a local traffic aggregation point that reduces the cost of internet transit for ISPs, since content and applications can be served from domestic servers rather than routed through distant international links. This lowers the marginal cost of delivering high-quality service and improves the return on investment for network operators expanding fixed infrastructure. This is essentially a two-sided network externality: cloud zones make broadband more valuable to consume, while simultaneously making broadband cheaper and more profitable to supply, and both the quantity and capacity of cloud zones contribute to this dynamic. The coefficients are smaller in comparison with the previous estimates for cloud and AI adoption. This may suggest that cloud zones act as a secondary (rather than a primary) driver of fixed broadband penetration.

Finally, results for mobile broadband adoption are reported in Table VI-6, following a similar empirical approach as in the fixed broadband case. The empirical specification to be estimated is presented as follows:

$$Log(MBB\ adoption_{it}) = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as mobile broadband price, GDP per capita (in lags), and mobile broadband speed.

In this case, results again point to a positive effect from cloud zones on mobile broadband adoption, although the coefficients are slightly smaller than in the case of fixed broadband, while the same happens with the significance levels (now 5% and 10%, depending on the specification). Results indicate that a new cloud zone deployed increases mobile broadband penetration by 0.16%, while a 1 MW increase in cloud zone capacity is associated with a 0.004% increase in mobile broadband penetration.

For mobile broadband, the impact mechanism may differ because the binding constraint on service quality is not last-mile capacity but backhaul and spectrum efficiency, both of which are directly affected by the presence of a local cloud zone. When content and applications are hosted locally rather than routed through international backhaul links, this materially improves the user experience for latency-sensitive mobile use cases such as video calls, mobile gaming, navigation, and app-based services. On the supply side, local cloud zones reduce the volume of traffic that mobile network operators must carry over expensive international backhaul and interconnection links, reducing costs. Moreover, because mobile broadband adoption is more prevalent among lower-income and price-sensitive users, the reduction in the cost of serving data-intensive content that cloud zones enable can translate into better quality-adjusted pricing and increased attractiveness of these services.

All in all, the analysis of the adoption layer for the selected four technologies points to positive and robust effects of cloud zone quantity and capacity on cloud computing, fixed and mobile broadband penetration. On the other hand, the effect for AI is positive only for cloud zone capacity, and when excluding the countries with the highest income per capita. Having identified positive effects of cloud zones on

technology adoption, the next step is to find out how much these technological adoption increases will translate into productivity gains.

Table VI-6. Drivers of mobile broadband adoption

Dep. variable: Log(MBB adoption)	(1)	(2)	(3)	(4)	(5)	(6)
Country sample	All	Excluding landlocked	All	All	Excluding landlocked	All
Cloud Zones t-1	0.0016*	0.0014**	0.0014*			
	[0.0008]	[0.0007]	[0.0008]			
Cloud Zones GW t-1				0.0401**	0.0360**	0.0347*
				[0.0201]	[0.0176]	[0.0196]
Log(MBB price)	-0.0074	-0.0076	0.0035	-0.0077	-0.0078	0.0045
	[0.0073]	[0.0070]	[0.0084]	[0.0074]	[0.0070]	[0.0084]
Log(GDPpc) t-1	0.1512*	0.1167	0.1592*	0.1528*	0.1171	0.1616*
	[0.0882]	[0.0850]	[0.0862]	[0.0890]	[0.0858]	[0.0864]
Log(MBB speed)	-0.0210	-0.0159	-0.0205	-0.0219	-0.0166	-0.0213
	[0.0250]	[0.0247]	[0.0237]	[0.0252]	[0.0248]	[0.0239]
Country Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones	Cloud Zones and MBB price	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW and MBB price
F-test first stage Cloud Zones t-1	76.88***	75.43***	113.08***			
F-test first stage Cloud Zones GW t-1				434.82***	404.76***	1133.11***
F-test first stage Log(MBB price)			75.83***			75.83***
Kleibergen-Paap F-stat	76.879	75.430	2.550	434.817	404.763	2.593
Hansen J stat p-value	0.1164	0.1147	0.2124	0.1137	0.1124	0.2023
Observations	311	279	311	311	279	311
R-squared (within)	0.5993	0.5864	0.5974	0.6005	0.5873	0.5979
Degrees of freedom	50	46	50	50	46	50
RMSE	0.0683	0.0708	0.0684	0.0682	0.0707	0.0684
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998). Source: Telecom Advisory Services analysis*

VI.2. The productivity layer

The model that measures the impact of digital adoption on productivity should include as regressors fixed and mobile broadband penetration, plus cloud and AI firm adoption. However, all four indicators are highly correlated, so including them jointly in the regression would produce severe multicollinearity, inflating standard errors, making coefficients unstable and sensitive to sample changes, and preventing an accurate interpretation of each individual coefficient. Beyond the collinearity problem, it would be challenging to find different instruments for each of the technologies. In light of these constraints, it is necessary to transform these variables into composite indicators.

To address this, we apply principal component analysis (PCA) and use the first principal component as a single composite index. This approach exploits the shared variance among the four original indicators, while discarding idiosyncratic measurement error specific to each variable. The dimension of the dataset is reduced by using only one or two of the estimated constructs; this also preserves degrees of freedom and yields more parsimonious and precise estimates. Even when using more than one construct, multicollinearity problems disappear, as these

factors are built by imposing orthogonality between them. Because PCA weights are data-driven rather than assigned arbitrarily by the researcher, the index avoids subjective weighting choices and is reproducible.

In this case, we will conduct estimates with one and two constructs, where reliability levels are acceptable (Cronbach's alpha = 0.64). It is important to note that only the first construct presents an eigenvalue higher than one, meaning that we can take as baseline estimates those that include only the first PCA component. Factor loadings and eigenvalues are presented in Tables A-2 and A-3 in the Appendix.

Digital adoption indicators may be endogenous to productivity because more productive economies are simultaneously more likely to self-select into adopting digital technologies (reverse causality), and because unobserved factors such as managerial quality or institutional strength jointly determine both productivity and digital adoption (omitted variable bias). This means that all estimates will be conducted through instrumental variables, using as instruments the adoption levels of a legacy technology (fixed telephony) with long-enough lags (values for 1990 and 1995), interacted with a time trend.[20] Fixed telephone penetration levels from decades ago proxy the density of the incumbent copper local-loop network (ducts, cabinets, exchanges) that operators subsequently reused and upgraded to deploy DSL/fiber broadband. Areas with a denser legacy telephone network therefore should experience faster and more extensive broadband-infrastructure rollout, giving the instrument strong predictive power for endogenous regressors associated with broadband or technology adoption. As the stock of fixed telephone lines was shaped several years ago by universal-service obligations, population density and voice-demand conditions that predate the current technologies, these technologically obsolete networks should not have any direct effect on present-day outcomes; the long lag also precludes reverse causality. First-stage estimates are presented in Table A-4 in the Appendix, demonstrating a strong predictive power of the instruments on the endogenous regressors.

The empirical specification for the productivity models to be estimated is presented as follows:

$$Log(Labor\ Productivity_{it}) = \beta(Digital\ Adoption_{it}) + \gamma Log(Capital\ per\ worker_{it}) + \lambda(Human\ Capital_{it}) + \alpha_i + \delta_t$$

$$Log(TFP_{it}) = \beta(Digital\ Adoption_{it}) + \lambda(Human\ Capital_{it}) + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects in each equation. Results are presented in Table VI-7, using both labor productivity (GDP per worker) and TFP as dependent variables. In all cases, results suggest a positive effect from digital adoption on productivity indicators. Results are verified using one and two

[20] We choose to use baseline telephone penetration interacted with linear time instead of full year fixed effect dummies, to prevent first-stage overfitting (and matrix singularity issues in the estimation of the first-stage standard errors).

PCA constructs, although the former have some advantages over the latter approach. First, interpretation is easier, not only because it consists of a single regressor (instead of two), but also because all digital variables have a positive weight in it (that is not the case with Digital PCA 2, as seen in Table A-3 in the Appendix).

Table VI-7. Drivers of productivity

	(1)	(2)	(3)	(4)
Dep. variable:	Log(Labor Productivity)		Log(TFP)	
Digital PCA 1	0.0217*	0.0519***	0.0205***	0.0289***
	[0.0126]	[0.0081]	[0.0039]	[0.0017]
Digital PCA 2		0.0944***		0.0244***
		[0.0195]		[0.0101]
Log(Capital per worker)	0.3385***	0.3883***		
	[0.0446]	[0.0389]		
Human Capital	0.0204***	0.0165***	0.0179***	0.0169***
	[0.0032]	[0.0017]	[0.0023]	[0.0020]
Country Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Endogenous regressors	Digital PCA 1	Digital PCA 1 and Digital PCA 2	Digital PCA 1	Digital PCA 1 and Digital PCA 2
F-test first stage Digital PCA 1	25.92***	25.92***	20.20	20.20***
F-test first stage Digital PCA 2		12.19***		8.86**
Kleibergen-Paap F-stat	25.918	39.411	20.201	19.630
Hansen J-stat p-value	0.1288	Exactly identified	0.2019	Exactly identified
Observations	194	194	194	194
R-squared (within)	0.4790	0.3235	-0.0063	0.0365
Degrees of freedom	41	42	40	41
RMSE	0.0220	0.0251	0.0189	0.0185
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998). Source: Telecom Advisory Services analysis*

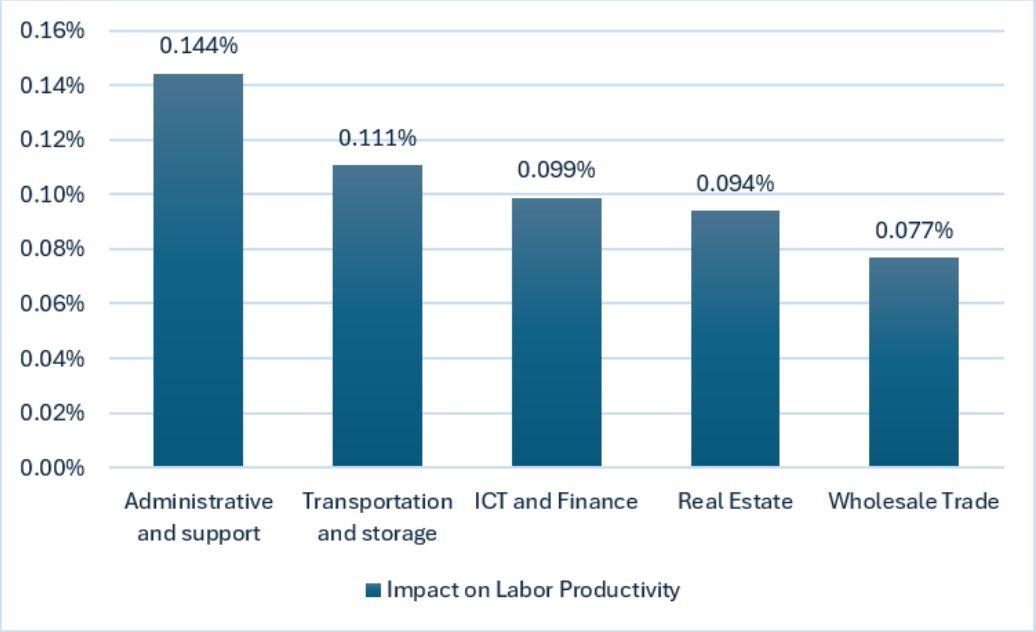
Under our preferred specification (using a single PCA component as a regressor), the coefficient presented in column (1) of Table VI-7 (0.0217) means that an increase of 1% in the digital adoption indicator (taking as baseline 2025 average values) will raise labor productivity by 0.022%. Similarly, the coefficient presented in column (3) of Table VI-7 (0.0205) means that an increase of 1% in the digital adoption indicator will raise TFP by 0.021%.[21]

Even if instruments used in the estimates reported in Table VI-7 behave well (they seem to be strong, and when it can be reported, the Hansen test does not reject the null hypothesis of their exogeneity), we still conducted some further robustness checks. In Table A-5 in the Appendix we estimated a specification including baseline GDP per capita interacted with time trend as a control variable, to make sure that the instrument is effectively isolating telecom-specific path dependency rather than capturing broader cross-country economic growth and convergence trends. Results confirm the findings of Table VI-7 for labor productivity and TFP.

[21] It is important to consider that a percentage change in a centered or standardized component (as PCA built indicators) is not automatically equivalent to a 1% change in the underlying adoption rates.

Estimates for impact on productivity levels were also conducted for sector-level regressions.[22] Results are detailed in Table A-6 in the Appendix.[23] Sectors analyzed include Accommodation and food services; Administrative and support services; Manufacturing and Construction; ICT and Financial activities; Professional, scientific and technical; Real estate; Retail trade; Transportation and storage; and Wholesale trade. In Graphic VI-1 we summarize the main findings, indicating labor productivity growth resulting from a 1% increase in the digital construct. The economic sector where this elasticity is the largest is that of Administrative and Support, followed by Transportation and storage, ICT and Finance, Real Estate and Wholesale trade. The other sectors analyzed showed statistically insignificant results, although in the case of Manufacturing and Construction the estimate cannot be considered conclusive as the instruments proved to be very weak in that case.

Graphic VI-1. Impact of a 1% digital adoption construct increase on labor productivity – by sector



Source: Telecom Advisory Services analysis

VI.3. Employment effects

After estimating productivity increases, it is also relevant to study if the increase in digital adoption triggered by data center deployment can affect employment levels. This analysis is done through IV with the same instruments as described earlier for the digital dynamic factor, but now using the local projection approach, in order to distinguish potential effects by year. This approach consists of estimating impulse response functions (IRFs) based on the local projections methodology first proposed by Jordà (2005).

[22] Sectoral-level digital dynamic factors use national-level fixed and mobile broadband penetration plus sector-specific cloud and AI penetration reported by the OECD.

[23] In this case, in the absence of sector-level lagged legacy technology indicators to use as instruments, we use as an instrument the average value of the digital construct in similar sectors but in other countries, by year. This instrument is introduced with one- and two-year lags.

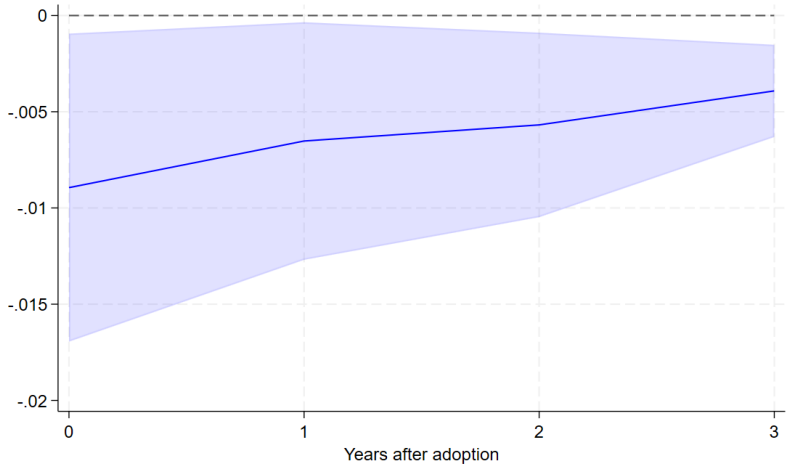
The empirical specification to be estimated is presented as follows:

$$Log(Employment_{it}) = \beta(Digital\ Adoption_{it}) + \gamma X_{it-1} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it-1} represents a vector of lagged controls. These controls include average wages, GDP, human capital, and lags of both the dependent and shock variables. The horizon length specified for the local projection analysis is from period 0 to period 3 after the digitization shock. Estimations are done considering the dependent variable in cumulative differences.

Graphic VI-2 presents the results that seem to indicate an initial negative effect followed by a recovery. This suggests that some diverse effects may take place over time regarding the link between digital adoption and employment. In particular, the results provide evidence of a short-run displacement, indicating that digital adoption initially substitutes for labor, as firms automate or digitize routine tasks (administration, back-office, basic customer service) and need fewer workers for the same output. After that initial effect, there seems to be a gradual recovery, as the negative effect fades over time. Several channels offset the initial loss. On the one hand, a productivity effect may take place: lower costs and better efficiency expand output and demand, which raises labor demand. Second, digital adoption creates complementary roles (data, IT, analytics, digital sales) that reinstate labor. Third, there may be some job reallocation, through which displaced workers move to other firms or sectors, and the economy adjusts. All in all, these results indicate that there is no clear evidence of permanent job destruction, as estimates converge toward zero by year 3.

Graphic VI-2. Impact of digital adoption increase on employment

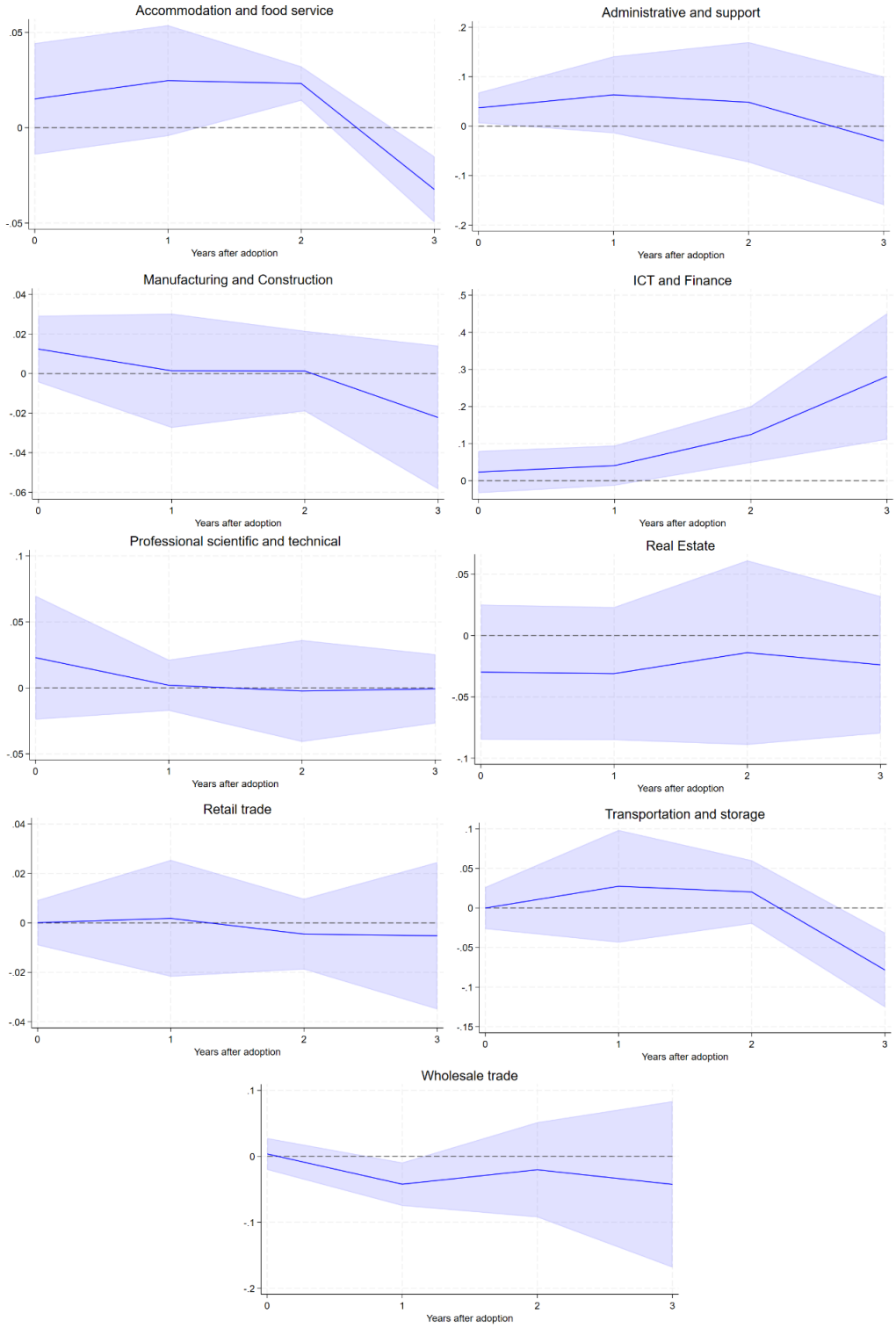


Source: Telecom Advisory Services analysis

These estimations are also conducted by sector. Results presented in Graphic VI-3 point to digital adoption generating some increases in employment in the ICT and Finance sectors, in Accommodation and Food services, while some reductions in employment are verified in Transportation and storage and Wholesale trade.[24]

[24] Still, it is important to remember that there are plenty of economic sectors not covered by the sectoral-level database, meaning that the slight reduction in overall employment levels presented in

Graphic VI-3. Impact of digital adoption increase on employment – by sector



Source: Telecom Advisory Services analysis

The sectoral results show that the small average employment decline found in the national-level estimates hides substantial heterogeneity, with the effects of digital

Graphic VI-2 may be attributed to some of these. Among not covered sectors we can find agriculture and fishing, mining, utilities, public administration, arts and recreation, and households.

adoption depending on how far each sector's tasks can be automated and how far adoption complements labor. The clearest positive effect is in ICT and Finance, where employment rises progressively and significantly, reaching about 28% by year 3, which is consistent with digital adoption expanding demand for technical, data and analytical roles in sectors where technology is at the core. In contrast, Transportation and storage and Accommodation and food service show initially positive or neutral responses followed by significant declines in year 3. This delayed pattern is consistent with a lagged displacement mechanism: firms first invest and expand, and once digital systems such as logistics automation, route optimization, online booking and self-service ordering are fully integrated, jobs are displaced.

VI.4. Mechanisms

The reduced-form model estimated in Section VI.1 links cloud zone deployments to digital adoption. These positive and significant effects are supposed to take place through several mechanisms that may be at work. These potential mechanisms were already depicted in Figure III-1 in Section III, although not estimated afterwards due to the empirical approach focusing on the reduced form. In this section we aim to explore these potential mechanisms, grouped into two categories: the effects on the creation of digital ecosystem companies (the "innovation" effect); and the effects on broadband infrastructure.

Starting with the first mechanism, data center infrastructure is expected to stimulate the development of digital industries, because it will be more attractive for them to deploy their services in countries with better conditions for data storage and processing facilities (for example, lower latency, better customer care). Digital industries are defined as companies that offer services beyond connectivity, such as cloud computing and AI solutions. These companies require the processing and storage capacity of large data centers in order to offer their services to retail consumers and firms. We estimate how cloud zone deployments (in both quantity of data centers and capacity associated with them) affect the creation of cloud, AI, Big Data, IoT and Fintech companies.

The empirical specification to be estimated is presented as follows:

$$Digital\ Companies_{it} = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote country and year fixed effects, while X_{it} represents a vector of controls, such as taxation, FDI, human capital and GDP per capita (in lags). The dependent variable is the number of digital companies per million inhabitants. Cloud zone variables are instrumented with the submarine cable indicators as above.

Table VI-8. Drivers of digital companies (firms per million people)

Dep. variable:	(1) Cloud companies	(2) AI companies	(3) Big Data companies	(4) IoT companies	(5) Fintech companies	(6) Cloud companies	(7) AI companies	(8) Big Data companies	(9) IoT companies	(10) Fintech companies
Cloud Zones t-1	0.0120**	0.3212***	0.0961***	-0.0001	0.0043					
	[0.0048]	[0.0211]	[0.0163]	[0.0016]	[0.0031]					
Cloud Zones GW t-1						0.3522***	9.3480***	2.8132***	-0.0053	0.1281*
						[0.1053]	[1.4196]	[0.1979]	[0.0507]	[0.0758]
Taxation	0.0132	0.0859*	0.0763	0.0525***	0.0148***	0.0141	0.1100***	0.0836	0.0524***	0.0151***
	[0.0120]	[0.0461]	[0.0742]	[0.0109]	[0.0054]	[0.0118]	[0.0335]	[0.0723]	[0.0109]	[0.0053]
FDI	0.0009	-0.0135	-0.0178**	-0.0035***	-0.0012	0.0009	-0.0138	-0.0179**	-0.0035***	-0.0012
	[0.0018]	[0.0114]	[0.0082]	[0.0006]	[0.0017]	[0.0018]	[0.0115]	[0.0082]	[0.0006]	[0.0017]
Human Capital	-0.3647**	-7.4988***	-5.6657***	-0.3413***	-0.0830	-0.3683**	-7.5889***	-5.6935***	-0.3412***	-0.0848
	[0.1441]	[0.1459]	[0.6673]	[0.0425]	[0.1353]	[0.1442]	[0.1848]	[0.6590]	[0.0431]	[0.1358]
Log(GDPpc) t-1	-1.7141	-22.1153	-1.6159	-1.1120	-0.3137	-1.6735	-21.0991	-1.3001	-1.1136	-0.2971
	[1.1813]	[14.1331]	[6.9709]	[0.7430]	[0.9312]	[1.1684]	[13.7648]	[6.9016]	[0.7468]	[0.9371]
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones	Cloud Zones	Cloud Zones	Cloud Zones	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW
F-test first stage Cloud Zones t-1	116.94***	116.94***	116.94***	116.94***	116.94***					
F-test first stage Cloud Zones GW t-1						11000.00***	11000.00***	11000.00***	11000.00***	11000.00***
Kleibergen-Paap F-stat	116.937	116.937	116.937	116.937	116.937	11000.000	11000.000	11000.000	11000.000	11000.000
Hansen J stat p-value	0.4049	0.1206	0.0666	0.7865	0.1026	0.4280	0.1711	0.0744	0.7861	0.1026
Observations	296	296	296	296	296	296	296	296	296	296
R-squared (within)	0.4669	0.5948	0.4492	0.5648	0.4049	0.4659	0.5875	0.4468	0.5649	0.4042
Degrees of freedom	49	49	49	49	49	49	49	49	49	49
RMSE	0.6863	6.1910	4.3540	0.5065	0.5128	0.6870	6.2460	4.3640	0.5065	0.5130
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Results using IV are presented in Table VI-8, pointing out that cloud zones trigger the increase of cloud, AI and Big Data companies. On the other hand, there are no significant effects on IoT companies and weak effects on Fintech companies. Therefore, cloud zone deployments do not affect all segments of the digital economy equally. In short, cloud infrastructure is a direct production input for cloud, AI, and Big Data firms, but only an indirect or partial input for IoT and Fintech firms, whose value proposition may depend on other complementary factors that cloud zones do not directly provide. AI companies show by far the largest coefficient, consistent with the earlier finding that AI is the most infrastructure-intensive: AI training and inference require GPU-intensive, high-throughput computing that is expensive to source internationally at low latency, so local capacity acts as a genuine enabling constraint. Big Data companies also react strongly to data center deployment because data-processing and analytics workloads require storage and compute proximity to the data being generated, so local cloud zones directly reduce their marginal cost of operating at scale.

On the other hand, IoT company formation may be driven by a different set of factors (hardware manufacturing costs, sensor and connectivity module prices, industrial adoption, and IoT applications) rather than by centralized cloud infrastructure, precisely to minimize latency and bandwidth costs. This means IoT firms are less dependent on the existence of a large, centralized cloud zone nearby. In turn, Fintech companies may be primarily driven by financial regulation, the size and maturity of the formal financial sector, smartphone penetration, and consumer trust or financial literacy—factors that are largely independent of local cloud infrastructure.

An important aspect that arises from the results presented in Table VI-8 is that the coefficients for cloud zone variables in the AI companies regressions appear to be large. This may be affected by the particular timing of the analysis, which coincided with a period of very fast expansion of AI technologies and companies.

Regarding the second group of mechanisms, it is also assumed that a relationship exists between data centers and broadband infrastructure. This implies that the development of data centers incentivizes the deployment of transport networks for data.

The empirical specification to be estimated in this case is presented as follows:

$$(BB\ infrastructure_{it}) = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as telecom regulation, population density, coverage levels (for speed equations), taxation, FDI, human capital and GDP per capita (in lags).[25] Cloud zone variables are instrumented with the submarine cable indicators as above.

[25] Dependent variables of coverage are introduced in levels (to avoid missing observations in which the value is zero), while both fixed and mobile broadband speeds are converted into logarithms.

Table VI-9. Drivers of broadband infrastructure indicators

Dep. variable:	(1) FTTH coverage	(2) 5G coverage	(3) Log(FBB speed)	(4) Log(MBB speed)	(5) FTTH coverage	(6) 5G coverage	(7) Log(FBB speed)	(8) Log(MBB speed)
Cloud Zones t-1	0.1419***	-0.2263	0.0023***	0.0112***				
	[0.0350]	[0.2032]	[0.0006]	[0.0029]				
Cloud Zones GW t-1					3.7590**	-5.8227	0.0596***	0.3254***
					[1.5299]	[6.6992]	[0.0177]	[0.0456]
Population density	0.7382***	0.2621			0.7355***	0.2661		
	[0.0892]	[0.1670]			[0.0899]	[0.1704]		
Δ Telecom regulation	-1.1033	-0.01915			-1.1324	0.0058		
	[0.8202]	[1.1721]			[0.8349]	[1.1737]		
FTTH coverage			0.0056***				0.0057***	
			[0.0006]				[0.0006]	
5G coverage				0.0027***				0.0027***
				[0.0006]				[0.0006]
Taxation	0.5255***	-0.4273	-0.0061***	-0.0020	0.5279***	-0.4349	-0.0060***	-0.0012
	[0.1397]	[0.4227]	[0.0021]	[0.0053]	[0.1424]	[0.4121]	[0.0021]	[0.0050]
FDI	0.0055	-0.0615***	0.0003	0.0000	0.0054	-0.0613***	0.0003	0.0000
	[0.0054]	[0.0234]	[0.0002]	[0.0001]	[0.0054]	[0.0232]	[0.0002]	[0.0001]
Human Capital	3.4287***	-4.7416***	0.0808***	0.0088	3.4068***	-4.7113***	0.0806***	0.0052
	[0.4432]	[1.0569]	[0.0109]	[0.0117]	[0.4461]	[0.9641]	[0.0111]	[0.0110]
Log(GDPpc) t-1	14.5684***	-47.0719***	0.3112	0.8814***	14.7187***	-47.1814***	0.3129	0.9141***
	[4.4447]	[8.0393]	[0.2682]	[0.2110]	[4.5870]	[8.2127]	[0.2690]	[0.2157]
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones	Cloud Zones	Cloud Zones	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW	Cloud Zones GW
F-test first stage Cloud Zones t-1	143.34***	132.69***	139.61***	136.91***				
F-test first stage Cloud Zones GW t-1					1868.67***	2207.58***	6456.58***	4056.42***
Kleibergen-Paap F-stat	143.341	132.686	139.609	136.910	1868.670	2207.575	6456.580	4056.422
Hansen J stat p-value	0.0774	0.0977	0.1042	0.1887	0.0761	0.0953	0.1038	0.2027
Observations	272	296	272	296	272	296	272	296
R-squared (within)	0.7994	0.8107	0.9379	0.9215	0.7985	0.8104	0.9383	0.9234
Degrees of freedom	48	51	47	50	48	51	47	50
RMSE	6.7690	18.4600	0.1418	0.1772	6.7850	18.4800	0.1413	0.1750
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Estimates conducted through IV models are presented in Table VI-9. We use as dependent variables two indicators of coverage of new-generation networks (FTTH and 5G), and also fixed and mobile broadband speeds to account for network performance.[26] Results point to a significant effect from cloud zone deployment (both in the number of data centers and capacity associated with them) on FTTH coverage, and on both broadband speed indicators.

The particularly strong effects on broadband speeds are consistent with cloud infrastructure creating demand for high-capacity connectivity, network densification and backbone/backhaul investments.

This creates incentives for telecommunications operators to conduct upgrades in broadband network capacity and quality. The positive effect on FTTH deployments is consistent with this interpretation. On the other hand, the analysis provides no evidence that cloud-zone expansion increases 5G coverage. Cloud infrastructure may create demand for network capacity, backhaul, latency improvements, and network quality, without necessarily requiring operators to expand 5G coverage geographically. In countries where 5G coverage is already widespread across the main urban areas, the relevant margin of adjustment may increasingly be capacity and speed rather than coverage.

VI.5. Negative externality

Beyond the gains in terms of productivity increases and GDP growth, another important effect to consider is the presence of potential negative externalities that have to be incorporated into the analysis.

These possible negative externalities can arise because large data centers are expected to consume large amounts of electrical energy, therefore potentially driving up local commercial electricity tariffs and crowding out non-digital industrial capital. This analysis will be conducted in two steps: first, we will estimate the extent to which cloud zones drive up electricity prices. Second, we will find out how much an increase in electricity prices contributes to reducing investment levels.

The first empirical specification to be estimated is presented as follows:

$$Log(Electricity\ price_{it}) = \beta(Cloud\ zones_{it-1}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as population, renewables share, and measures of electricity supply (measured through coverage and TWh generated). Cloud zone variables are instrumented with the submarine cable indicators as above.

In the IV estimates we conducted in Table VI-10 we were able to verify that a new cloud zone being deployed is associated with an increase in electricity prices of

[26] We decided not to simulate the effects on 4G coverage as the period of analysis is contemporaneous with the progressive decline of this technology as 5G was entering into its expansive phase.

0.95%, while every extra MW of cloud zone capacity is related to an increase of 0.03% in electricity prices.

As expressed above, this increase in electricity prices is expected to have negative effects on the economy, potentially crowding out investment initiatives that otherwise may have taken place.

Table VI-10. Drivers of electricity price

Dep. variable: Log(Electricity price)	(1)	(2)
Cloud Zones t-1	0.0095**	
	[0.0045]	
Cloud Zones GW t-1		0.2601*
		[0.1378]
Population	-0.1034***	-0.1053***
	[0.0092]	[0.0091]
Δ Renewables	0.0041	0.0042
	[0.0047]	[0.0047]
Electricity coverage	-0.1080**	-0.1044**
	[0.0461]	[0.0440]
Electricity generated	-0.0003	0.0005
	[0.0005]	[0.0004]
Country Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Endogenous regressors	Cloud Zones	Cloud Zones GW
F-test first stage Cloud Zones t-1	9.01***	
F-test first stage Cloud Zones GW t-1		6.35***
Kleibergen-Paap F-stat	9.011	6.348
Hansen J stat p-value	0.1475	0.1530
Observations	309	309
R-squared (within)	0.3655	0.3590
Degrees of freedom	51	51
RMSE	0.2732	0.2746
Method	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Next, we also conduct a regression linking electricity prices with investment (Table VI-11), following the empirical specification:

$$Log(Investment_{it}) = \beta log(Electricity\ prices_{it}) + \gamma X_{it} + \alpha_i + \delta_t$$

Where α_i and δ_t denote respectively country and year fixed effects, while X_{it} represents a vector of controls, such as taxation, FDI, interest rates, saving rates, and GDP per capita (lagged).

Results verify that a 1% increase in electricity prices will reduce investment levels by 0.027%. This reduced investment will reduce capital stocks, which will further negatively affect GDP. Therefore, the impact on GDP will have to consider this negative externality, calculated as the investment crowded out due to higher electricity prices, with the addition of the extra GDP loss because of the negative impact on capital stocks (for this purpose, we consider than the results of the γ

parameter in Table VI-7, which represents the capital share on the income under the assumption of constant returns to scale in capital and labor).

All in all, the GDP spillovers will be calculated as follows:

$$GDP\ impact = Increased\ Labor\ Productivity * Workers - Externality$$

Where all three terms on the right-hand side of the equation (labor productivity, quantity of workers and negative externality) are affected by cloud zone deployments according to the results of this research.

Table VI-11. Drivers of Investment

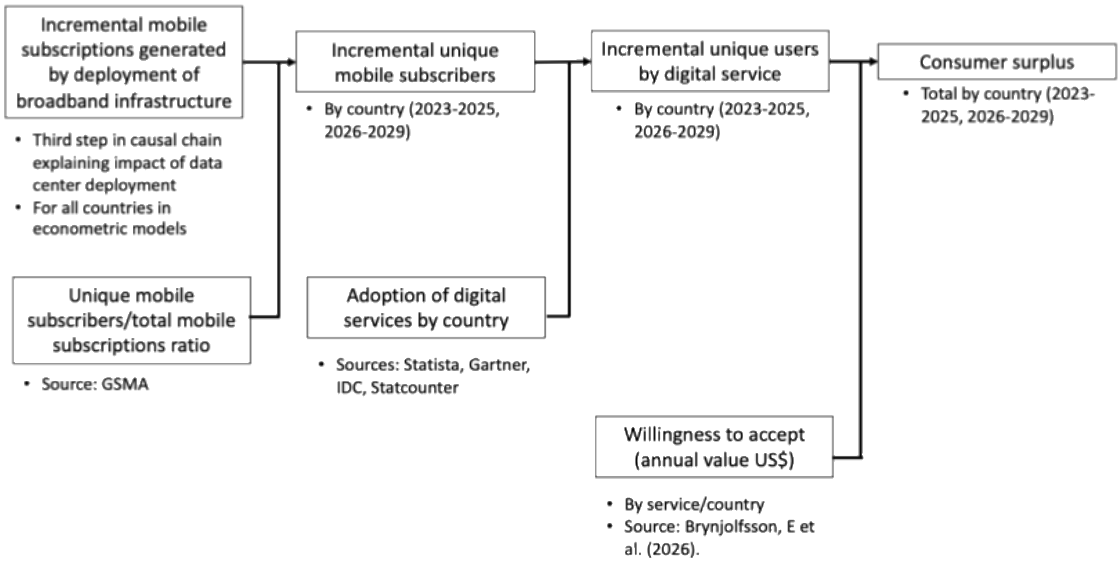
Dep. variable: Log(Investment)	
Log(Electricity price)	-0.0273**
	[0.0121]
Industry	-0.0089*
	[0.0045]
Taxation	-0.0099***
	[0.0021]
FDI	0.0001
	[0.0002]
Interest rate	-0.0016
	[0.0019]
Savings rate	0.0092***
	[0.0029]
Log(GDPpc) t-1	-0.2048
	[0.1276]
Country Fixed Effects	YES
Year Fixed Effects	YES
Observations	416
R-squared (within)	0.1913
Degrees of freedom	54
RMSE	0.0916
Method	OLS

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively.*
Robust standard errors in brackets (Driscoll and Kraay, 1998).
Source: Telecom Advisory Services analysis

VI.6. Estimation of consumer surplus

The estimation of consumer surplus follows the steps presented in Figure VI-2.

Figure VI-2. Estimation methodology for consumer surplus



The first step in calculating the consumer surplus consists of estimating the incremental unique mobile subscribers yielded by additional broadband adoption triggered by the deployment of a data center. According to the causal chain depicted in Figure VI-2, the development of broadband infrastructure resulting from data center deployment stimulates broadband adoption. The econometric model predicts adoption as measured by total mobile broadband subscriptions (per 100 people). However, this metric could potentially overestimate the number of subscribers, and consequently the estimation of consumer surplus, due to dual phone usage behavior (for example, enterprise cellphones and consumer cellphones). Therefore, total mobile broadband subscriptions need to be converted to a more precise indicator: unique mobile subscribers. This conversion should eliminate enterprise mobile subscribers, since consumer surplus should be driven exclusively by consumer usage. The conversion is done by relying on the ratio unique mobile subscribers/total mobile subscriptions as calculated for each country by the GSMA. Along these lines, for the purpose of the analysis, we rely on the incremental number of unique mobile subscribers generated by the development of broadband infrastructure triggered by data center deployment.

The incremental unique mobile subscribers will serve to calculate the consumer surplus generated by the deployment of data centers. For this purpose, we rely on a study developed by Brynjolfsson et al. (2026)[27] where the willingness to accept money (for the average citizen) for giving up the use of a digital platform for a month is estimated based on survey data.

To estimate consumer surplus, we multiply: 12 (number of months) * (Consumer surplus monthly) * (New Users) * (Share of the population that uses each digital service).

[27] Brynjolfsson, E., Collis, A., Liaqat, A., Kutzman, D., Garro, H., Deisenroth, D. and Wernerfelt, N. (2026) *The digital welfare of nations: new measures of welfare gains and inequality*. National Bureau of Economic Research (May).

Finally, considering that our study addresses other nations beyond the ones covered by the Brynjolfsson et al. (2026) study, we assume similar willingness to pay for geographically and culturally similar nations (see Table VI-12).

Table VI-12. Study and country extensions relied upon for the current study

Country in survey	Countries addressed in study
Belgium	Belgium, Netherlands, Luxembourg
Canada	Canada
France	France
Germany	Germany
Ireland	Ireland
Japan	Japan, Taiwan, Australia, Singapore
Mexico	Chile, Uruguay
Norway	Norway, Denmark, Finland, Sweden
Romania	Poland,
South Korea	Malaysia, India, Thailand
Spain	Spain
United Kingdom	United Kingdom
United States	United States

Source: Brynjolfsson et al. (2026); Telecom Advisory Services analysis

VII. CONCLUSIONS

Through this study we assessed the economic impact of data center development. For that purpose, we sketched a causality chain framework identifying all the mechanisms through which data centers can impact the economy, and to test them empirically we built a data panel covering the period 2015-2025 for a sample of 39 countries from different regions of the world (Western and Eastern Europe, North and Latin America, Asia Pacific and the Middle East). Data center infrastructure was measured through the number of cloud zones located in cloud regions, including hyperscaler, edge, and GPU infrastructures; and by a proxy of the country-level capacity in these infrastructures. Econometric models were estimated primarily through IV approaches, with country and year fixed effects.

Our results confirmed that data center infrastructure stimulates the development of a country's digitization, resulting in a significant economic contribution through productivity spillovers, which in turn yield GDP growth.

The different causal effects in the framework that were tested can be summarized in Table VII-1, with results confirming most of them.

Table VII-1. Hypotheses tested

Model	Item	Hypothesis	Results	Remarks
Reduced form specification	1	Data centers → Cloud penetration	Verified (positive)	Effect takes place through SMEs, not the big firms
	2	Data centers → AI penetration	Verified (positive)	Effect takes place when richer countries are omitted, and only through SMEs, not the big firms.
	3	Data centers → BB penetration	Verified (positive)	For both fixed and mobile broadband
	4	Digital adoption → Productivity	Verified (positive)	The impact is heterogeneous by sector
Employment	5	Digital adoption → Employment	Verified (negative)	While being negative, the impact is heterogeneous by sector
Mechanisms	6	Data centers → Digital companies	Verified (positive)	For cloud, AI and Big Data companies; weak evidence for Fintech companies and no significant effect for IoT companies
	7	Data centers → BB infrastructure	Verified (positive)	For FTTH coverage and broadband speeds (not for 5G coverage)
Negative externality	8	Data centers → Electricity price	Verified (positive)	This suggests investment crowding out effects that have to be accounted for in the simulation
	9	Electricity price → Investment	Verified (negative)	

Source: Telecom Advisory Services analysis

The multiple effects identified can be quantified in terms of elasticities for the average country in the sample:

Table VII-2. Impact of data center deployment in an average country

Model	Item	Hypothesis	Claim
Reduced form specification	1	Data centers → Cloud penetration	• A 1% increase in cloud zone capacity raises cloud adoption by 0.0571% (*)
	2	Data centers → AI penetration	• A 1% increase in cloud zone capacity raises AI adoption by 0.5891% (except in ADCs) (*)
	3	Data centers → BB penetration	• A 1% increase in cloud zone capacity raises FBB adoption by 0.0176% (*) • A 1% increase in cloud zone capacity raises MBB adoption by 0.0145% (*)
	4	Digital adoption → Productivity	• A 1% increase in cloud zone capacity raises labor productivity by 0.0136% in LDCs and MDCs (0.0020% in ADCs) • A 1% increase in cloud zone capacity raises TFP by 0.0129% in LDCs and MDCs (0.0019% in ADCs)
Employment	5	Digital adoption → Employment	• A 1% increase in cloud zone capacity reduces employment by 0.0056% in LDCs and MDCs (0.0008% in ADCs), although in the following years employment levels are recovered.
Mechanisms	6	Data centers → Digital companies	• A 1% increase in cloud zone capacity raises the number of cloud companies by 0.0105% (*) • A 1% increase in cloud zone capacity raises the quantity of AI companies by 0.1178% (*) • A 1% increase in cloud zone capacity raises the quantity of Big Data companies by 0.0496% (*) • A 1% increase in cloud zone capacity raises the quantity of Fintech companies by 0.0066% (*)
	7	Data centers → BB infrastructure	• A 1% increase in cloud zone capacity raises FTTH coverage by 0.0172% (*) • A 1% increase in cloud zone capacity raises FBB speeds by 0.0216% (*) • A 1% increase in cloud zone capacity raises MBB speeds by 0.1180% (*)
Negative externality	8	Data centers → Electricity price	• A 1% increase in cloud zone capacity raises electricity prices by 0.0943% (*)
	9	Electricity price → Investment	• A 1% increase in cloud zone capacity reduces investment by 0.0006%
End-to-end effects		Data centers → GDP	• A 1% increase in cloud zone capacity increases GDP by 0.0113% in LDCs and MDCs (0.0011% in ADCs) (*)
Consumer surplus		Data centers → increase in consumer surplus due to adoption of digital services	• The deployment of digital services triggered by an increase in cloud zone capacity will increase consumer surplus resulting from an increase in adoption of digital services

Note: Baseline values for the calculation of these elasticities are those of the average country in the sample.
LDCs: Less developed countries (up to 33p of income per capita in the first year of sample)
MDCs: Moderately developed countries (33p-66p of income per capita in the first year of sample)
ADCs: Highly developed countries (from 66p of income per capita in the first year of sample)
Source: Telecom Advisory Services analysis

An important result of the study was the verification of heterogeneous effects by country (the impact is larger in less advanced economies) and by type of firm adopting technology (which means that the economic contribution is mostly

generated through SMEs rather than through larger firms). This means that SMEs have a key role in this process. On average, they represent more than 97% of the total firms with more than 10 employees in the sample of countries analyzed, meaning that the bulk of the digital transformation effects triggered by cloud zones take place through these companies.

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Appendices

Table A-1. First stages for cloud adoption

	(1)	(2)	(3)	(4)
Dep. variable:	Cloud Zones t-1	Cloud Zones t-1	Cloud Zones GW t-1	Cloud Zones GW t-1
Submarine cables t-3	0.9148***	0.1779	0.0344***	0.0012
	[0.1888]	[0.1804]	[0.0100]	[0.0084]
Capacity of submarine cables t-3	0.5059***	9.0732***	0.0186***	0.3312***
	[0.1418]	[0.7070]	[0.0063]	[0.0273]
Submarine cables t-3 x Income < median		1.1615***		0.0572***
		[0.1777]		[0.0070]
Capacity of submarine cables t-3 x Income < median		-9.3673***		-0.3425***
		[0.7538]		[0.0248]
Log(Cloud ARPU)	-1.8408	-1.0339	-0.0912	-0.0697
	[1.3224]	[1.3059]	[0.0553]	[0.0613]
Log(Income per firm) t-1	-0.2367	2.7486	-0.0310	0.0809
	[1.7638]	[2.1038]	[0.0786]	[0.0911]
Log(FBB speed)	2.1101	1.6774**	0.1059	0.0757**
	[1.2833]	[0.7284]	[0.0619]	[0.0375]
Log(MBB speed)	1.3342	0.7733	0.1011**	0.0772*
	[1.1150]	[1.0040]	[0.0445]	[0.0422]
Log(FBB speed) x Income < median	-3.0280	-0.2801	-0.1053	-0.0076
	[2.3266]	[1.3539]	[0.0889]	[0.0629]
Log(MBB speed) x Income < median	-0.2494	-0.3730	-0.0354	-0.0525
	[1.4297]	[0.8264]	[0.0601]	[0.0368]
Human Capital	0.6973***	0.2167**	0.0277***	0.0136**
	[0.08287]	[0.0883]	[0.0020]	[0.0055]
Human Capital x Income < median	-0.2600	-0.4133	0.0077	-0.0131
	[0.6357]	[0.3132]	[0.0379]	[0.0182]
Country Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	231	231	231	231

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Table A-2. Principal components/correlation

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.70729	0.725699	0.4268	0.4268
Comp2	0.981594	0.090946	0.2454	0.6722
Comp3	0.890648	0.470184	0.2227	0.8949
Comp4	0.420464	.	0.1051	1

Source: Telecom Advisory Services analysis

Table A-3. Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
Log(MBB adoption)	0.3472	0.3655	0.8621	-0.0513	0
Log(FBB adoption)	0.3175	0.7950	-0.4498	0.2546	0
Log(AI adoption)	0.6471	-0.1640	-0.2332	-0.7071	0
Log(Cloud adoption)	0.5999	-0.4555	-0.0093	0.6577	0

Source: Telecom Advisory Services analysis

Table A-4. First stages for productivity equations

Dep. variable:	(1) Digital PCA 1	(2) Digital PCA 2
Fixed telephone adoption 1990 x time-trend	-0.0260***	0.0110***
	[0.0047]	[0.0025]
Fixed telephone adoption 1995 x time-trend	0.0270***	-0.0133***
	[0.0055]	[0.0028]
Log(Capital per worker)	3.2591***	-2.157***
	[0.6852]	[0.2828]
Human Capital	-0.0840***	0.0318***
	[0.0265]	[0.0095]
Country Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	194	194

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Table A-5. Drivers of productivity – robustness check

Dep. variable:	(1) Log(Labor Productivity)	(2) Log(TFP)
Digital PCA 1	0.0546***	0.0448***
	[0.0156]	[0.0098]
Digital PCA 2	0.1013***	0.0677***
	[0.0350]	[0.0232]
Log(Capital per worker)	0.3975***	
	[0.0584]	
Human Capital	0.0167***	0.0176***
	[0.0023]	[0.0018]
Log(GDPpc 1995) x time-trend	0.0005	0.0025*
	[0.0017]	[0.0015]
Country Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Endogenous regressors	Digital PCA 1 and Digital PCA 2	Digital PCA 1 and Digital PCA 2
F-test first stage Digital PCA 1	24.42***	13.68***
F-test first stage Digital PCA 2	14.01***	17.08***
Kleibergen-Paap F-stat	32.474	36.400
Hansen J-stat p-value	Exactly identified	Exactly identified
Observations	194	194
R-squared (within)	0.2828	-0.1654
Degrees of freedom	43	42
RMSE	0.0258	0.0204
Method	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998).*
Source: Telecom Advisory Services analysis

Table A-6. Drivers of labor productivity – by economic sector

Dep. variable: Log(VA/worker)	(1) Accommodation and food service	(2) Administrative and support	(3) Manufacturing and Construction	(4) ICT and Finance	(5) Professional, scientific and technical	(6) Real Estate	(7) Retail trade	(8) Transportation and storage	(9) Wholesale trade
Log(Capital per worker)	0.4349***	0.2128**		0.5639***	0.3796***	0.8517***	0.2728**		
	[0.0724]	[0.0899]		[0.0943]	[0.0992]	[0.0346]	[0.1321]		
Human Capital	0.0234***	0.0400***	0.0565***	0.0289***	-0.0155	0.1056**	0.0376***	0.0954***	0.1917***
	[0.0053]	[0.0111]	[0.0038]	[0.0057]	[0.0107]	[0.0449]	[0.0072]	[0.0188]	[0.0382]
Digital PCA 1	0.0085	0.1474***	-0.0073	0.0569***	0.0370	0.0941***	0.0179	0.1496**	0.0724***
	[0.0148]	[0.0280]	[0.1099]	[0.0290]	[0.0368]	[0.0227]	[0.0191]	[0.0744]	[0.0200]
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
F-test of excluded instruments in first stage (Digital PCA 1)	17.51***	17.01***	2.04	6.91**	5.74**	7.87**	39.89***	12.88***	13.27***
Kleibergen-Paap F-stat	17.506	17.012	2.035	6.906	5.743	7.873	39.888	12.881	13.273
Hansen J-stat p-value	0.9818	0.2770	0.6798	0.2601	0.4277	0.1761	0.3707	0.7753	0.4160
Observations	146	145	403	141	153	114	64	187	151
R-squared (within)	0.7943	0.3195	0.1973	0.5794	0.2486	0.6312	0.3152	0.2499	0.3199
Degrees of freedom	33	32	68	34	31	29	20	38	34
RMSE	0.0842	0.0508	0.0677	0.0529	0.0571	0.0547	0.0582	0.0987	0.0807
Method	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML	IV-LIML

*Note: ***, **, * denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors in brackets (Driscoll and Kraay, 1998). Considering that the Capital per worker regressor is not available for the complete sample, we removed this control when we found that it was insignificant in earlier estimates, to maximize sample size.*

Source: Telecom Advisory Services analysis