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Economic spillovers from cloud computing: evidence from OECD countries

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ABSTRACT
The objective of this paper is to estimate the impact of cloud computing on economic performance. The analysis relies on a multi-equation model in which cloud computing is complementary with broadband to maximize the economic contribution of digital technologies. The proposed model is estimated for a sample of OECD countries, depicting cloud penetration at the sector level. Our results suggest positive effects from cloud adoption on economic outcomes. However, the impact of cloud computing depends on broadband penetration and cloud adoption, which, as expected, vary by country and industry. The sector benefitting from the largest economic impact is information and communications, followed by manufacturing, while in contrast, no impact was detected for the transportation sector. This is one of the first empirical analysis estimating cloud economic spillovers on an aggregated basis, from which important public policy implications can be derived to stimulate the development and adoption of this technology.

KEYWORDS
Cloud computing; broadband; ICT; economic performance; productivity

1. Introduction

Digital technologies are transforming the way businesses are being managed, creating new opportunities for reducing communication costs, promoting data analysis, enhancing operational optimization, and lowering the entry barriers to new markets.

From an academic viewpoint, the quantification of the economic impact from digital technologies has captured the attention of several researchers through decades. Once the so-called *Productivity Paradox* appeared to be resolved, the bulk of the research has been able to verify the positive effects that these technologies have on firms' performance. That said, the type of digital tools being assessed has evolved through the years, in parallel with the development of new technologies. Thus, the academic interest has shifted focus from general Information Technologies (ITs) (Braunstein, 1985; Brynjolfsson & Yang, 1997), to broadband (Katz, 2012; Koutroumpis, 2009) and more recently, to the adoption of novel digitization services and applications.

Among the latest digital advances, cloud computing has introduced a significant transformation in the delivery of IT-based services, providing a remote environment for sharing and accessing computing resources. Investment on cloud technology is considered crucial for the development of the digital economy. Modern production systems are increasingly based on connectivity between people, machines, and real-time data. In this context, limited cloud infrastructure can be assumed to be a barrier for the digital transformation (AWS, 2021). According to IDC, the 2021 worldwide public cloud market amounts to USD 426.80 billion, being its growth rate largely unaffected by

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COVID-19. In fact, the pandemic business disruption has rather enhanced cloud adoption as organizations have accelerated new digital service creation and migrated applications from private to shared infrastructure.

Considering the potential of cloud computing to enable firm's access to several digital services, it is reasonable to expect that an important value is generated at the enterprise level in terms of efficiencies and cost reductions, which should turn into aggregated economic effects. As most empirical studies conducted to date have focused on the microeconomic impact of cloud adoption on firm's rate of innovation and cost efficiency, a relevant related question that needs to be addressed is the aggregate impact of an infrastructure that is so central to the digital economy. Given the importance that digital transformation has for the development of national economies, it is also critical to understand in quantitative terms what the contribution of public cloud is to metrics such as value creation and productivity. In addition, heterogeneities in the economic impact by industrial sectors have not been deeply studied to date. In the same way broadband does not have the same economic impact on manufacturing when compared to agriculture, one should not expect cloud computing fulfill homogeneous contribution to value creation in both sectors. An empirical understanding of these issues should provide useful inputs to policymakers and academics alike.

This paper presents an estimation of cloud's contribution to economic output at the industry-level for a sample of OECD countries. As its basic level, the approach to be used is based on the original framework created by Röller and Waverman (2001) for telephony services, and later adapted by Koutroumpis to fixed broadband (2009), consisting of a production function framework within a structural econometric model that endogenizes ICT related variables. We upgrade the original approach developed by these authors by introducing in the production function an additional digital variable, cloud computing, that plays a complementary role with broadband. In addition, we also add more granularity to the evidence by conducting the analysis at the industry level, thus being able to differentiate cloud's economic impact by sector. Finally, we further adapt the original framework, by measuring the effects over three different output measures, such as Gross Value Added (GVA), Labour Productivity, and Total Factor Productivity (TFP).

The remaining of the paper is structured as follows. In section 2 we present the main aspects of cloud computing. Section 3 reviews the research literature on the impact of cloud on firm's performance and national economies conducted to date. In section 4 we develop a theoretical model that introduces cloud computing into established frameworks developed to study the effects of broadband on economic output. Section 5 presents the data to be relied upon for modeling its economic impact, with a detailed explanation of the constructed variables and the related sources. Section 6 presents the results from the econometric estimations. Finally, Section 7 concludes and develops the main implications of the study findings.

2. Definitions

Cloud computing is considered a fundamental revolution in delivering IT-based services. It provides a remote access environment for sharing and accessing computing resources such as servers, storage spaces and network service applications with high reliability, and scalability to large and small enterprises, start-ups, governments, and public agencies (Ebadi & Jafari Navimipour, 2019; Khayer et al., 2020; Naseri & Jafari Navimipour, 2019; Park & Ryoo, 2013; Vu et al., 2020).

From an infrastructure standpoint, it represents a combination of technological tools that allows the remote access of computing services through internet, rather than using a firm's own IT infrastructure, containing a physical and an abstraction layer. The first one comprises the hardware resources, including servers, storage, and network components. The abstraction layer includes software deployed across the physical layer (Mell & Grance, 2011). The cloud platform relies on several technologies ranging from virtualization, grid computing, micro-services architecture, and high-speed broadband (Byrne et al., 2017). With regards to the last technology, the reduction of any network traffic limitations (from technological to regulatory barriers) multiplies the fundamental benefits of cloud computing. This highlights the complementarity between broadband and cloud computing.[1]

According to PwC (2021) and Chen et al. (2022), cloud service characteristics include On-Demand self-service; Metered Service; Rapid Scaling; Resource Pooling; and Broad network access. There are different computing products that can be supplied within cloud services, although Software as a Service (SaaS), where software is licensed on a subscription basis and is centrally hosted, is usually considered the most complete of them. Beyond these offerings, a further distinction is made among different cloud services regarding deployment models, depending on the location of the infrastructure (Frontier Economics, 2022; PWC, 2021), although the most common is that of Public Cloud, where providers manage all the computing infrastructure and sell their service to the users.

3. Review of the research on the economic contribution of cloud computing

As anticipated in the introduction, the emergence of cloud computing as a critical infrastructure has yielded several academic studies focused on assessing its economic contribution. While the research evidence generated so far is primarily focused on understanding the impact of public cloud on firm performance, a few studies present findings on its economic effects on a more aggregated basis.

3.1. Microeconomic benefits of cloud computing

Cloud services present the advantage that users can access technology services on an as-needed basis from a service provider (Frontier Economics, 2022). When cloud computing was not available as a commercial service, enterprises requiring these resources had to build their own data centers, purchase the required hardware and software, and hire skilled workers for its development and running. As a result, most companies were unable to enjoy the economies of scale and innovation advantages provided by this technology.

With the commercial availability of cloud services, these infrastructures became reachable to many firms, especially small and medium enterprises. Moreover, this technology provides convenient access to powerful computational resources through the network at minimal cost (Khayer et al., 2020; Marston et al., 2011; Sheikholeslami & Navimipour, 2017). In addition, market entry barriers are lowered by allowing firms immediate access to cloud-supported services, rather than incurring months or years as required to build their own infrastructure.

For a firm, adopting cloud computing services can add value at both strategic and operational levels, increasing revenues and minimizing costs (Carcary et al., 2014). These benefits have been identified by some authors as improved organizational flexibility, higher IT-capabilities, and shared resources and collaborative environment, enabling firms to achieve better performance (Armbrust et al., 2010; Chen and Wu, 2013; Chen et al., 2022). Flexibility in accessing data enabled by cloud technology can be crucial for firms, not only in terms of specific decentralized functions, but also to facilitate employees' access from anywhere, something that is particularly important in today's hybrid working world (Frontier Economics, 2022). In addition, cloud adoption can prompt the transformation of firms' IT departments, moving their primary emphasis from regular maintenance to business assistance, and improving both intra- and inter-firm collaborations, thereby facilitating innovation (Berman et al., 2012; Chen et al., 2022; Luo et al., 2018; McAfee, 2011). As a result of all these effects, Berman et al. (2012) argue that cloud computing can basically shift the competitive landscape of industries. Frontier Economics (2022) also argue about the potential of cloud to improve organizational resilience, by means of additional security support, offered through dedicated staff, and infrastructure support. Moreover, cloud's back-up capabilities can offer protection against disruption caused by shock events or cybersecurity threats.

In addition, cloud services can help businesses achieve IT efficiency (Oliveira et al., 2014), due to the use of scalable technical resources (Marston et al., 2011), improving efficiency in work (Low et al., 2011) and increasing service availability (Armbrust et al., 2010). On the other hand, cloud computing is expected to increase business agility, because of the capacity for deploying mass computing technology quickly, minimizing capital costs, and responding rapidly to market changes (Oliveira et al., 2014).

However, the success of cloud services in improving firm performance can be conditioned to certain internal factors. As pointed out by Khayer et al. (2020), the successful implementation depends on the system quality, the firm's organizational IT capability, and on end-user feedback. Similarly, some authors argue that the adoption of cloud services requires some internal transformations to maximize its impact, such as training workers (Armbrust et al., 2010; Chen et al., 2022).

3.2. Empirical research on the microeconomic effects of cloud adoption

Most empirical studies of the economic impact of cloud computing have been conducted at the firm-level, and in many cases focused on specific economic sectors. The selected variables to measure firm performance vary by study, being in some cases productivity, innovation, or other metrics based on financial indicators.

Schniederjans and Hales (2016) rely on transaction cost economics and examine how cloud computing supports adequate supply chain collaboration and is positively associated with the economic and environmental performance of firms. Data for this study was generated by 247 survey responses on IT and supply chain professionals and was analyzed using structural equation modeling. The authors found that, with interoperability, cloud computing positively improves collaboration among supply chain partners and drives a firm economic performance. Similarly, Loukis et al. (2019) conducted a survey of 102 Dutch firms and concluded that both operational and innovational benefits of SaaS cloud technologies can yield a positive impact on business performance, as measured by improved operations and the rate of innovation. Their contribution, however, is that the magnitude of impact is mediated by the firm's absorptive capacity, defined as a company's ability to recognize, acquire, and incorporate useful new knowledge from the external environment, and to make valuable innovations in processes, products, and services. Coincidentally, Chou et al. (2017) analyzed a sample of 165 firms in the IT, travel, tourism, finance, and banking industries in Taiwan, finding a positive association of cloud adoption with service innovation. Bolwin et al. (2022) conducted a large-scale survey of 1504 companies in Germany aimed at quantifying the impact of AWS cloud computing in business performance. By extrapolating the survey results to the overall firm population, they estimate that 1.25 million companies in Germany rely on the cloud, realizing added value growth of euros 11.2 billion by using AWS technologies.

In a similar vein, other authors have focused on analyzing which are the necessary factors that enhance the firm-level impact of cloud. For example, Garrison et al. (2015) analyzed a survey of 302 Korean businesses with a structural equation modeling methodology and found that managerial, technical, and relational IT capabilities can be factors which positively contribute to cloud computing's impact on firm performance. However, managerial capability appeared to have the largest contribution.

As better datasets were developed, research on the microeconomic benefit of cloud computing has extended to emerging countries as well. For example, Kathuria et al. (2018) analyzed a survey of 147 Indian firms, finding that firms can capitalize on cloud computing to enhance performance and propose a strategic value appropriation path for adopters to improve their business performance. In particular, the authors highlight cloud technological and integration capability, cloud service portfolio capability, and business flexibility as enablers of cloud's impact on firm performance. In turn, Dalenogare et al. (2018) analyzed the impact of several digital services, including cloud computing, on some firm performance metrics for a sample of Brazilian firms (product, operational, and side-effects expected benefits), finding a positive link. Khayer et al. (2020) found a positive impact of a cloud computing construct on a firm performance construct for a sample of Chinese firms during the period 2018–2019, using structural equation modeling. In particular, the authors argue about the relevance of external factors, such as end-user satisfaction, which contributes to firm performance.

On a worldwide scale, Chen et al. (2022) estimated for a world sample of firms during the period 2010–2016 the link between cloud computing and some firm-level performance metrics (such as ROA and Tobin's Q). They use Difference-in-Difference econometric techniques, finding a positive relation: firms adopting cloud computing experience significantly improved profitability and market value. In addition, the authors identify differences in cloud computing performance impact by industry type and firm size. Their results point to manufacturing firms having larger profitability after cloud service adoption in comparison with service firms.

3.3. Aggregate macroeconomic impact of cloud computing

Empirical academic research aimed at quantifying cloud's macroeconomic impact is much scarcer. That said, some evidence exists in working papers and consultancy reports. In an OECD working paper, Gal et al. (2019) estimated the impact of cloud computing (among other technologies) on productivity growth for a sample of 20 European countries, using a combination of firm-level and industry-level data, sourced from Eurostat and the Orbis database and applying it to a Neo-Schumpeterian growth approach that links innovation and technology diffusion. Their results suggest that a 10-percentage point increase in adoption of cloud computing would translate into an increase in multifactor productivity growth by 0.9 percentage points. The authors found that economic gains are strongest for high productive enterprises. An interesting result from this study is that cloud computing presents the strongest impact on productivity performance for the case of the smallest firms, which can avoid the fixed costs of investing in data storage and processing facilities, in other words a way to acquire 'scale without mass,' according to the authors.

Similarly, a report from Frontier Economics (2022) used a conservative approach based on Gal et al. (2019) results to find out that a 10% increase in the adoption of cloud in the Irish public sector could generate productivity benefits in the order of 473 million euros in the first year alone following adoption. Their estimate assumes that the productivity effect is going to be 'half' (0.45%) of the one estimated by Gal et al. (2019). By multiplying the productivity growth by firms' sales, they calculate the economic benefit cited above.

Beyond the impact on national productivity, there is limited quantification of the aggregated effects on aggregated output at a national level. One reason for the limited research is that cloud computing constitutes an intermediate input to sector output and, as such, is not usually measured in national accounts. However, estimates were conducted by factoring in the impact of cloud investment on overall sector output. For example, AWS investment in Indonesia (USD 5 billion) between 2022 and 2037 is estimated to generate USD 11 billion in spending on construction, labor, materials, specialized software, and personnel, as well as additional value to the country's information sector.[2] A similar estimate was derived by PWC (2021) for Indonesia.

3.4. Macroeconomic impact channels of cloud services

Before attempting to estimate the impact of cloud computing on economic output it is important to synthesize existing research reviewed above and formalize a set of hypotheses that allows understanding of why is it possible to causally link both terms. Figure 1 presents the set of factors that could explain why the adoption of cloud computing can be linked to economic activity.

The first effect is associated to conventionally understood as linked to infrastructure deployment capital spending. The investment linked to the construction of data centers in an economy drives direct, indirect, and induced multipliers, as calculated in input/output tables. In the first place, data center construction drives investment to build the facility. In addition, data center construction has an impact on indirect spending (such as upstream buying and selling of intermediate inputs). Finally, the household spending based on the income generated from direct and indirect jobs

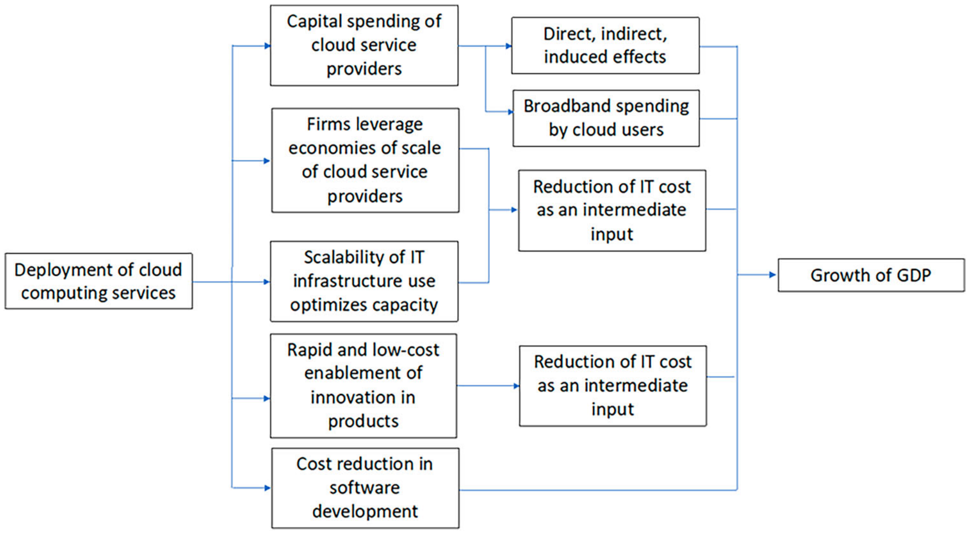

Figure 1. Casual links between cloud computing and economic growth.
Source: Authors' elaboration based in the reviewed literature.

drives induced multipliers. This is precisely the analysis of impact of cloud computing on the Indonesian economy (AWS, 2021), by isolating it from other effects and generating the estimation using input/output tables.

The second effect of cloud computing on output is derived from the microeconomic benefit of the service on acquiring organizations (in other words, private enterprises, and government agencies). Cloud computing provides these customers with advantages in cost, flexibility, and scalability. The opportunity is then to automatically scale storage and software use to quickly up and down in response to load to save resources (Armbrust et al., 2010). A reduction in resource spending has an impact on firms' margins and consequently monetary value, which translates into economic contribution.

The third effect has been studied through survey data reviewed above proving that SaaS has an impact on firms ICT-enabled innovation (Chen et al., 2022; Chou et al., 2017; Kathuria et al., 2018), although the effect appears to be moderate, according to Loukis et al. (2019), and PWC (2021).

Finally, cloud services have an important economic contribution to software development. As stipulated by Byrne et al. (2017), when cloud vendors adopt technologies that enable them to develop products 'higher up the stack' and offer services with greater abstractions, the work of software development is simplified, since they can focus only on code programming and its deployment, lowering development costs. This, in turn, leads again to higher margins and, potentially an increase in sales.

In sum, a combination of all four effects has a spillover impact on economic growth. This should be added to actual sales of cloud service providers in the national economy.

4. Empirical approach

4.1. Baseline approach

As mentioned above, the approach to be used in this paper is inspired on Röller and Waverman (2001) and Koutroumpis (2009) and consists of a structural econometric model with a production function and a supply and demand framework that endogenizes ICT-related variables. This framework was originally developed as a mean to mitigate the common critique of reverse causality resulting from procedures based on simple Ordinary Least Squares (OLS) single-equation estimations. In our case, this could mean that both broadband and cloud computing may be potentially endogenous. To control for this concern, the framework proposed by Röller and Waverman (2001) and Koutroumpis (2009) captures these two-way relationships between growth and ICTs, by explicitly disentangling the values in a simultaneous equations model.

In a departure from the prior research, however, we argue that this framework can be further modified to identify the specific effects of other digital technologies beyond broadband, such as cloud computing. Under this approach, the industrial aggregate economic output (Y) is related, via a production function, to the stock of physical capital (K), the human resources employed (L), plus both ICT variables, broadband (BB), and cloud computing (CLOUD). Both broadband and cloud variables are defined in terms of firm penetration, thus representing a measure of stock rather than investment, as highlighted by Koutroumpis (2009).

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

Table 1. System of simultaneous equations.

Aggregate production equation		$Y_{ist} = f(K_{ist}, L_{ist}, BB_{ist}, CLOUD_{ist})$
Broadband equations	Demand equation	$BB_{ist} = g(INCOME_{ist}, BB\ PRICE_{ist}, HK_{ist}, R\&D_{ist}, URBAN_{it})$
	Supply equation	$BB\ INV_{ist} = h(BB\ PRICE_{ist}, BB\ COMP_{it})$
	BB infrastructure production	$\Delta BB_{ist} = j(BB\ INV_{ist})$
Cloud equations	Demand equation	$CLOUD_{ist} = k(INCOME_{ist}, CLOUD\ PRICE_{ist}, HK_{ist}, R\&D_{ist}, URBAN_{it})$
	Supply equation	$CLOUD\ INV_{ist} = v(CLOUD\ PRICE_{ist}, CLOUD\ COMP_{it})$
	Cloud infrastructure production	$\Delta CLOUD_{ist} = z(CLOUD\ INV_{ist})$

Note: i, s, and t denote respectively country, sector, and year.
Source: authors' elaboration.

The broadband demand equation models broadband penetration (BB_{ist}) as a function of the average income per firm ($INCOME_{ist}$), the price of a standard broadband service ($BB\ PRICE_{ist}$), the degree of human capital endowment at the industry (HK_{ist}), the intensity of research and development ($R\&D_{ist}$), and the percentage of the urban population ($URBAN_{it}$). The supply equation links the aggregate broadband investment associated to a specific industry ($BB\ INV_{ist}$) to broadband price levels ($BB\ PRICE_{ist}$), and competition intensity in the telecom market ($BB\ COMP_{it}$).[3] These variables affect the dynamic of the supply side of the market. The infrastructure equation models the annual change in broadband penetration (ΔBB_{ist}) as a function of broadband investment ($BB\ INV_{ist}$). In that sense, the difference in penetration levels is assumed to be a function of the infrastructural change that is already used by an industry.

Up to this point, we have followed the Koutroumpis (2009, 2019) framework. From now on, we mirror the approach followed for the case of broadband, to endogenize cloud penetration as well. This means that we are introducing specific equations linked to cloud demand, cloud supply, and cloud infrastructure production. In that sense, cloud demand ($CLOUD_{ist}$) is expected to depend on the average income per firm ($INCOME_{ist}$), on cloud prices ($CLOUD\ PRICE_{ist}$), on the degree of human capital (HK_{ist}), on research and development intensity ($R\&D_{ist}$), and on the degree of urbanization ($URBAN_{it}$). As for the cloud supply equation, it links cloud investment ($CLOUD\ INV_{ist}$) as a function of cloud prices ($CLOUD\ PRICE_{ist}$) and the competitive intensity in the local cloud sector ($CLOUD\ COMP_{it}$). Finally, the variation in cloud penetration ($\Delta CLOUD_{ist}$) is modelized to depend on cloud investment ($CLOUD\ INV_{ist}$).

In sum, the enhancement over the original Koutroumpis (2009) framework takes place over three main areas. First, it introduces in the production function an additional digital variable beyond broadband, which is cloud computing. By introducing cloud computing, the model allows disentangling a key broadband complementary technology. Second, this analysis is conducted at the industry level, rather than nationally. In doing so, the model sheds light on divergent sector technology effects. Third, we introduce different output measures at the aggregate production equation, by allowing estimation of Gross Value Added, Total Factor Productivity (TFP), and Labor Productivity. This is relevant as these different output measures explain different perspectives of firm performance: value added is a metric of aggregate value that producers add to the goods and services they have purchased, labor productivity measures the value of production by the average worker, while TFP measures how much the representative firm extracts from all its input factors. This is described in the following sections.

4.2. Production function to measure economic output (GVA)

The empirical strategy selected for this research is supported by a theoretical model that introduces spillover effects in the macroeconomic output derived from public cloud adoption.[4] In this case, our purpose is to tease out the different economic effects that occur once cloud providers have deployed infrastructure in a country. Under this scenario, the indirect effects capture the spillover of cloud services on the rest of the economy. For example, a particular spillover is considered when cloud services enable the adoption of IT services in the SME sector, which benefits from the scalability of IT state-of-the-art.

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

$$GVA_{ist} = A_{ist} K_{ist}^{\alpha} L_{ist}^{\beta} \tag{1}$$

where *GVA* represents gross value added, *K* is the physical capital stock, and *L* is labor. Subscripts *i, s* and *t* denote, respectively, countries, sector, and time periods. The term *A* represents the TFP, reflecting differences in productive efficiency.

Naturally, TFP is expected to depend on digital technologies. However, if we were to proxy ICT with only a cloud-related variable, it would result in the problem of omitted variable bias. In other words, the contribution of cloud computing would capture the effects of other digital technologies, such as broadband, which needs to be isolated. Therefore, we propose a different approach, modeling broadband as an enabler of the economic impact of cloud adoption. This is reasonable as both technologies are largely complementary, in fact, without broadband, cloud is not expected to yield any economic impact.

Therefore, we expect TFP to depend on broadband adoption by firms (denoted by BB), and beyond it, we can assume that a higher cloud penetration (CLOUD), as a variable measuring adoption, will enhance that impact. This is reasonable as cloud is expected to enhance the contribution of all other digital applications and uses, addressed here under the broadband indicator. As a result, TFP is proposed as:

$$TFP_{ist} = \Omega_i \zeta_s \psi_t BB_{ist}^{\Phi + \delta CLOUD_{ist}} \tag{2}$$

According to it, TFP depends on country-level time-invariant characteristics represented by a fixed effect Ω_i, capturing idiosyncratic productivity effects. In addition, ζ_s captures sector-level unobservables that make some industries more productive than others. Finally, ψ_t captures year effects, absorbing exogenous technological developments not associated to digitalization, plus cyclical economic shocks affecting all the sample economies.[5]

As it is assumed that broadband connectivity contributes to increased productivity, we expect a positive value for Φ. As another important aspect that could shape the impact of broadband on country-level productivity is cloud penetration, the empirical exercise will consist in identifying the sign and significance level of the parameter δ. If we verify that $\delta > 0$, this means that CLOUD enhances the positive impact of broadband. This would mean that, for two countries with the same broadband penetration, we expect to observe a larger economic impact for that one with higher adoption of cloud services. Inserting Equation (2) into (1), we obtain:

$$GVA_{ist} = \Omega_i \zeta_s \psi_t BB_{ist}^{\Phi+\delta CLOUD_{ist}} K_{ist}^{\alpha} L_{ist}^{\beta} \tag{3}$$

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

$$\log(GVA_{ist}) = \mu_i + \eta_s + \chi_t + \alpha \log(K_{ist}) + \beta \log(L_{ist}) + \Phi \log(BB_{ist}) + \delta CLOUD_{ist} \log(BB_{ist})$$

where $\mu_i = \log(\Omega_i)$ is a country-level fixed effect, $\eta_s = \log(\zeta_s)$ represents the sector unobservables, while $\chi_t = \log(\psi_t)$ captures time-related effects. Thus, we understand that the evolution of *GVA* depends on some specific unobserved characteristics, on the capital stock, on labor, on broadband penetration and, most importantly for our purposes, on public cloud adoption.

From the last equation, we can calculate the economic impact of broadband, which is expected to depend on the adoption of cloud services:

$$\frac{\partial \log(GVA_{ist})}{\partial \log(BB_{ist})} = \Phi + \delta CLOUD_{ist}$$

Similarly, we can directly calculate the economic contribution of CLOUD because of spillover effects on the economy's productivity:

$$\frac{\partial \log(GVA_{ist})}{\partial \mathrm{CLOUD}_{ist}} = \delta \log(BB_{ist})$$

This means that the impact of CLOUD on the GVA is expected to depend on the advancement of broadband infrastructure. In other words: a lack of broadband diffusion will limit the impact of cloud. This means that, if broadband adoption is constrained, for instance, by high telecommunications prices, the positive impact of cloud is diminished.

4.3. Model transformation to measure effects on labor productivity

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

$$GVA_{ist} = \Omega_i \zeta_s \psi_t BB_{ist}^{\Phi+\delta CLOUD_{ist}} K_{ist}^{\alpha} L_{ist}^{1-\alpha}$$

which means we can manipulate that expression to represent it as:

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

So effectively, labor productivity (measured as GVA per worker) can be expressed as a function of the unobservable factors, broadband and cloud penetration, plus the physical capital stock per worker. Applying logs for linearization, we get the empirical specification for our second output measure to be introduced into the multi-equation model:

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

4.4. Effects on total factor productivity

Recall Equation (2), that represents the measure of TFP as a function of the unobservable indicators, broadband, and cloud computing penetration. Applying logs and rearranging:

$$\log(TFP_{ist}) = \mu_i + \eta_s + \chi_t + \Phi\log(BB_{ist}) + \delta CLOUD_{ist}\log(BB_{ist}) \quad (4)$$

Which represents the third empirical specification.

A relevant thing here is the determination of a TFP indicator to be used in the empirical estimation, as this is not an observable variable. The most common approaches are based on the estimation of a production function as a first step and obtaining the TFP as a residual in a second step. In doing so, we considered diverse methodologies, such as a simple residual from a fixed effects estimated production function, and the approach proposed by Olley and Pakes (1996). We describe these approaches in the next subsections.

4.4.1. TFP calculated as a residual of a fixed effects production function

This approach consists of two steps. First, we estimate a Cobb–Douglas production function where *GVA* depends on *K* and *L*. We include fixed effects in the estimation, to control for country and year unobservable heterogeneity. From that production function, TFP is calculated as a residual using the estimated parameters, therefore: $\log(TFP) = \log(GVA) - [\alpha\log(K) + \beta\log(L) + \textit{Fixed Effects}]$. This approach has been followed, for instance, in Ahmed (2017), among many other researchers. Contrary to Ahmed (2017), we do not include the ICT variables in the first-step estimation of the production function as we aim to use these variables to explain the TFP (the residual). Once the TFP has been extracted as a residual, in the second step Equation (4) can be estimated.

Including fixed effects is an advantage over the standard OLS approach as it contributes to control a part of the bias derived from the correlation between unobservable productivity shocks and input levels. However, it may seem unrealistic to assume that all the unobserved productivity is time-invariant, being thus necessary to explore further approaches.

4.4.2. TFP calculated following Olley and Pakes

Olley and Pakes (1996) developed an estimator using investment as a proxy for unobservable shocks affecting productivity.[6] We used the Gross Capital Formation indicator reported by the OECD statistics to account for investment. In the first step, the production function is calculated. After the estimation of the production function following, TFP was calculated as a residual.

4.5. Link with alternative approaches

Our approach implies some differences with the usual research literature on economic growth that is worth addressing. First, our analysis is based on estimating effects on value-added rather than on overall output as most empirical research on economic growth has usually done.[7]

In addition, data limitations prevented us to deliver an approximation that can explicitly account for cloud effects on medium or long-term economic growth, as the reduced timeframe of the data available makes it unsuitable for that purpose. Moreover, our empirical estimation will not be conducted for output growth rates. Thus, while our model can be used to simulate a certain spillover effect associated with a point-in-time increase in cloud penetration, further research will have to be done in the future to account for longer growth effects.

Literature on economic growth and development usually has been mostly based on Solow frameworks, mainly presenting economic growth, rather than levels, as a dependent variable for empirical estimates. In the past, this literature has been used to modeling the role of innovation (Aghion & Howitt, 1992), human capital (Mankiw et al., 1992), institutions and social capital (Hall & Jones, 1999), and capital externalities (Rebelo, 1991; Romer, 1986); thus, being feasible for the purpose of studying the role of digital technologies. Another field of this related literature is that of studying convergence through growth regressions (Barro & Sala-i-Martin, 1992; Sala-i-Martin, 1996), although this approach is beyond the scope of our analysis and inappropriate for the dimensions of our dataset.

Finally, recent advances in the literature of growth accounting can also be considered for future research in the economic role of cloud computing. For example, Ahmed (2021) proposed a growth accounting framework that follows two steps: first, the author proposes an econometric model of economic growth to identify the key parameters, while conducting additional checks to validate the results. In the second step, he calculates the TFP indicator following the standard growth accounting approach, while also proposing an empirical framework to estimate capital productivity. This approach has been used to analyze the role of Foreign Direct Investment (Ahmed, 2021; Lashaki & Ahmed, 2017), green productivity (Ahmed, 2020a), bioeconomy (Ahmed, 2018), the digital economy (Ahmed, 2020b), and Cybersecurity (Ahmed, 2021) spillovers.

5. The dataset

Having formalized the models, we now describe the data to be used in the analyses. The sample, determined by the data availability, consists of an unbalanced panel at the industry level for 19 OECD countries covering the period 2016–2020.[8] Table 2 summarizes the variable description and sources.

Table 2. Variable description.

Variable	Description	Source
GVA	Gross Value Added at constant prices (2017 million USD)	OECD/IMF
K	Fixed assets at constant prices (2017 million USD)	OECD/IMF
L	Total persons employed (in thousands)	OECD
BB	Fixed broadband > 30 Mbps penetration (% firms)	OECD
Cloud	Business purchasing cloud services (% firms)	OECD
BB price	Average price of unlimited fixed broadband plan > 30 Mbps (as % of firm value added per worker)	Telegeography/ OECD
Cloud price	Indicator based on average broadband commercial plan and the price of Local Access all metro area cost of a Fast Ethernet (100 Mbs circuit) for 0–5 km range (as % of firm value added per worker)	Telegeography/ OECD
HK	Businesses which employ ICT specialists (% firms)	OECD
HHI	Herfindahl-Hirschman Index for fixed broadband	OVUM/TAS
Urban	Urban population (% of total population)	World Bank
R&D	Binary variable identifying all sectors where investment in R&D is equal or above 2% of the value added.	OECD
Revenue	Value added per firm at constant prices (2017 USD)	OECD
BB investment	Average investment by fixed broadband line multiplied for the number of subscriptions at industry level (constant prices 2017 USD).	ITU/OMDIA/OECD
Cloud investment	Average investment by cloud commercial subscription multiplied by the number of firms connected to cloud at the industry level (constant prices 2017 USD).	Oxford Economics/ OECD
Cloud companies	Number of cloud companies every million inhabitants	Crunchbase
Cloud zones	Binary variable identifying if the country has been selected by global cloud providers as a hub to deploy cloud regions	Telegeography

Source: authors' elaboration.

Main industry economic indicators (GVA, K, L) were extracted from the OECD stats database. GVA and fixed assets were originally denominated in constant prices of the local currencies, with varying base years. In order to accommodate those variables into a homogeneous metric, we converted them to US dollars and unified 2017 as the base year.[9]

As for the digital-related variables, both broadband and cloud penetration levels were obtained from OECD statistics contained in the *ICT Access and Usage by Businesses* database. Broadband is measured as the share of firms subscribing to a connection offering at least 30 Mbps of download speed.[10] As for cloud penetration, it is measured as the share of firms purchasing cloud services.[11]

Broadband price was compiled from Telegeography and is measured as the average price for unlimited commercial plans offering at least 30 Mbps speed. Cloud price is more complicated to measure, although an accurate approximation can be those of average commercial broadband plans (for small and medium firms), and the price of local access to all metro area cost of a fast ethernet (100 Mbs circuit) for 0–5 km range (for larger firms). Thus, we built a price indicator for cloud based on both indicators (source: Telegeography) weighted respectively according to the share of firms by size within each combination of industry, country, and year.[12] In both cases, prices are measured in terms of affordability (as % of the average firm value added per worker).

Human capital is a variable used as a driver of digital demand, so it is defined as the share of businesses employing ICT specialists (source: OECD). To account for competition intensity, we used the Herfindahl-Hirschman Index for fixed broadband, while for the case of cloud it was not possible to apply a similar metric due to unavailability of data for market shares. Therefore, we measure competition intensity in the cloud industry by the number of companies offering cloud services every million inhabitants (source: Crunchbase), and by the presence of cloud regions developed by global operators (source: Telegeography). Urban population was measured in terms of percentage, with data reported by the World Bank.

Broadband investment data comes from the International Telecommunication Union database, although some transformations had to be made. Since the objective is to compute broadband investment associated to a specific industrial sector, an aggregated metric is not accurate. First, we calculated the investment associated only to the fixed telecommunications segment, by multiplying aggregate telecommunication investment by the share of investment attributable to fixed services according to OMDIA. Next, we divided the fixed investment over the total number of broadband lines at the national level. By doing so, we estimate a value of the average investment per broadband line, which is later multiplied by the number of broadband lines within each economic industry.[13]

Finally, cloud investment associated to each industrial sector was calculated as follows. From Oxford Economics, the share of GDP attributable to cloud companies' investment was used to obtain a national-level figure of cloud investment.[14] This value was divided by the number of national commercial cloud firms compiled from OECD, yielding a unit value of average investment. Next, we multiplied the average investment per cloud subscription by the number of firms contracting cloud services within each sector. In both broadband and cloud investment, values were deflated to be measured in constant 2017 dollars.

6. Results

First, we present the estimation for the baseline model, focusing on the average effect of cloud connectivity on GVA, labor productivity, and TFP. All estimates include country, year, and sector dummies.[15] Afterwards, we explore heterogeneities by economic sector.

6.1. Baseline results

Results are reported in Table 3. In column [I] we introduce cloud penetration to the original Koutroumpis (2009) model, although considering it first as exogenous. The results for the main equation are in line with the expectations, with both physical capital and labor coefficients being positive and significant, without rejecting the null hypothesis of constant returns to scale (according to the z-stat provided to test if $\alpha + \beta = 1$). The estimated α, that measures the share of capital returns over the income, seems like the usual 1/3 typically arising from national accounts (slightly above, but not far).

Table 3. 3SLS fixed effects estimate.

Variables	[I]		[II]		[III]		[IV]		[V]	
Dependent variable:	Log(GVA)		Log(GVA)		Log(GVA/L)		Log(TFP-FE)		Log(TFP-OP)	
Log(K)	0.3934***	(0.0235)	0.4093***	(0.0245)						
Log(K/L)					0.4083***	(0.0237)				
Log(L)	0.6027***	(0.0385)	0.5876***	(0.0396)						
Log(BB)	0.4075***	(0.1487)	0.4421***	(0.1498)	0.4933***	(0.1224)	0.4273***	(0.1284)	0.6655***	(0.1265)
Log(BB)*Cloud	0.0018***	(0.0005)	0.0017***	(0.0005)	0.0016***	(0.0004)	0.0011**	(0.0004)	0.0009**	(0.0004)
Dependent variable: Log(BB)										
Log(P_{BB})	−0.0360**	(0.0162)	−0.0518***	(0.0169)	−0.0434**	(0.0170)	−0.0409**	(0.0168)	−0.0433***	(0.0167)
Log(HK)	0.0854***	(0.0219)	0.2284***	(0.0151)	0.2160***	(0.0152)	0.2123***	(0.0151)	0.2118***	(0.0151)
Log(VA per firm)	0.0372**	(0.0179)	0.0257	(0.0180)	0.0447**	(0.0185)	0.0680***	(0.0182)	0.0546***	(0.0182)
R&D	−0.0213	(0.0257)	0.1002***	(0.0257)	0.1002***	(0.0257)	0.0985***	(0.0253)	0.1029***	(0.0253)
Urban	−0.0362	(0.0334)	−0.0109	(0.0360)	−0.0026	(0.0360)	−0.0023	(0.0355)	−0.0004	(0.0355)
Dependent variable: Log(BB inv.)										
Log(P_{BB})	−0.1420***	(0.0433)	−0.1456***	(0.0360)	−0.1380***	(0.0359)	−0.0883**	(0.0361)	−0.1137***	(0.0360)
HHI	0.0001	(0.0005)	0.0002	(0.0003)	0.0001	(0.0003)	0.0002	(0.0003)	0.0002	(0.0003)
Dependent variable: Log(BB/L.BB)										
Log(BB inv.)	−0.0717***	(0.0161)	−0.0584***	(0.0157)	−0.1190***	(0.0197)	−0.1251***	(0.0197)	−0.1232***	(0.0196)
Dependent variable: Log(Cloud)										
Log(P_{CLOUD})			−0.0218	(0.0187)	−0.0185	(0.0189)	−0.0201	(0.0189)	−0.0206	(0.0189)
Log(HK)			0.3443***	(0.0206)	0.3337***	(0.0208)	0.3323***	(0.0207)	0.3324***	(0.0208)
Log(VA per firm)			0.0417*	(0.0235)	0.0477**	(0.0241)	0.0691***	(0.0240)	0.0547**	(0.0241)
R&D			0.0755**	(0.0362)	0.0724**	(0.0365)	0.0708*	(0.0364)	0.0732**	(0.0365)
Urban			0.0866*	(0.0502)	0.0874*	(0.0502)	0.0887*	(0.0501)	0.0883*	(0.0502)
Dependent variable: Log(Cloud inv.)										
Log(P_{CLOUD})			−0.1335***	(0.0382)	−0.1231***	(0.0384)	−0.0961**	(0.0383)	−0.1166***	(0.0384)
Cloud companies			0.0073	(0.0809)	−0.0062	(0.0807)	−0.0156	(0.0806)	−0.0134	(0.0807)
Cloud zones			0.0243	(0.1227)	0.0398	(0.1224)	0.0337	(0.1223)	0.036	(0.1225)
Dependent variable: Log(Cloud/L.Cloud)										
Log(Cloud inv.)			−0.0245	(0.0176)	0.0036	(0.0288)	−0.006	(0.0287)	0.0009	−0.0287
Z stat for $\alpha+\beta=1$	−0.11		−0.08		N.A.		N.A.		N.A.	
Treatment for Cloud	Exogenous		Endogenous		Endogenous		Endogenous		Endogenous	
R-squared†	0.969		0.965		0.932		0.500		0.534	
Observations	552		517		517		517		517	

Note: *$p < 10\%$, **$p < 5\%$, ***$p < 1\%$. †Refers to first equation of the structural model. All equations in all estimates include country, year, and sector dummies.
Source: authors' elaboration.

In addition, the results point to a positive and significant effect for broadband. The impact coefficient (0.41) is slightly larger than the largest one reported by Koutroumpis (0.33), although it is important to remind some differences in both models that are worth explaining. First, the dependent variable is different. Koutroumpis relies on national GDP, while we use industry-level GVA, that can be considered as a more accurate output measure since it does not consider intermediate inputs. Second, the broadband variable differs considerably. While Koutroumpis measures broadband penetration as the standard ITU definition per inhabitants, we rely on a fast-speed 30 Mbps definition penetration, at the firm level. This means that our measure does not consider residential broadband, only industrial, and for fast connections, that are usually the ones that yield the larger economic impact. Therefore, it is not surprising that the economic effect yields a higher coefficient.

Cloud penetration (in interaction with broadband) presents a positive and highly significant coefficient (at 1% level), suggesting that it is effectively enhancing the economic effects of broadband. However, this result should be taken with caution as they are not yet addressing the potential endogeneity associated to cloud penetration. As for the remaining equations, results are in line with the expectations. Particularly, broadband demand depends positively on firm's revenue and human capital, while it depends negatively on the service price. In addition, broadband investment is negatively associated with price, as in Koutroumpis (2009).

Next, in column [II] we endogenize cloud penetration, thus estimating the complete set of seven equations as proposed in Table 1. Again, the null hypothesis of constant returns on scale on capital and labor cannot be rejected. Now the coefficient for the interacted cloud decreases marginally with respect to column [I], while the significance level remains unchanged.

As for the cloud-related equations, demand seems to depend positively on the human capital endowment at the industry level, on firm's income, on R&D activity, and on urbanization, while the coefficient for cloud price is negative but not significant, suggesting demand insensitive to price differentials. The fact that cloud demand depends positively on firm's income (measured as value added per firm) means that the suspected reverse causality is effectively taking place, and thus, controlling for endogeneity seems necessary. As for cloud investment, it depends negatively on prices (similar as the case of broadband) while competition indicators seem to be insignificant in this sample.

In column [III] we turn to the labor productivity measure. As constant returns to scale on capital and labor stand in previous estimations, the transformation of the production function to represent labor productivity (measured as GVA per worker) is accurate. The estimated α remains almost unchanged with respect to the previous columns. As expected, labor productivity depends positively on both broadband and cloud penetration. This means that cloud computing is relevant not only to explain aggregated output, but also because of its influence on productivity levels. No major changes arise in the secondary equations of the model.

Finally, in columns [IV] and [V] we introduce as dependent variable the estimated measures of TFP, following the fixed-effects (TFP-FE) and Olley and Pakes (TFP-OP) approaches. Again, both broadband and cloud technology seem to influence positively these productivity metrics,[16] although some important comments should be made. First, the coefficient for broadband remains stable in the TFP-FE model, while increases with respect to previous estimates in the case of TFP-OP. Second, the coefficient associated to the interacted cloud diminishes significantly in both TFP-FE and TFP-OP models with respect to the previous values. This seems to suggest that, while relevant for both measures of productivity, cloud effects seem to be slightly stronger for the case of labor productivity than for TFP, where in contrast, other digital tools englobed in the broadband indicator seem to prevail. These results point that cloud computing may be more relevant for more efficient use of labor rather than from other inputs.

To understand the magnitude of the economic effect associated to cloud penetration, recall that the coefficients presented in Table 3 above cannot be interpreted directly as elasticities, as some further algebra is needed. As seen in section 4, and replacing $\delta = 0.0017$ as estimated in column [II]:

$$\frac{\partial \log(GVA_{ist})}{\partial \mathrm{CLOUD}_{ist}} = 0.0017*\log(BB_{ist})$$

From where the elasticity between GVA and cloud penetration can be obtained:

$$\frac{\partial GVA_{ist}}{GVA_{ist}}\frac{\mathrm{CLOUD}_{ist}}{\partial \mathrm{CLOUD}_{ist}} = 0.0017*\log(BB_{ist})*\mathrm{CLOUD}_{ist}$$

According to it, the elasticity will depend on the estimated coefficient (0.0017), and on the actual penetration levels of broadband and cloud. This means that each country-industry combination will have its own elasticity level to determine the magnitude of the spillovers. For the average observation during 2021 (simple average of broadband and cloud penetration), we can conclude that an increase of 1% in cloud penetration will yield a GVA increase of 0.33%. A similar exercise can be done for the case of labor productivity and TFP, by using the estimated coefficients from columns [III], [IV], and [V] of Table 3. Accordingly, for the average country in the sample, an increase of 1% in cloud penetration will result in 0.31% increase in labor productivity, while the effect on TFP will range between 0.22% (TFP-FE) and 0.18% (TFP-OP).

In order to highlight the differences between the sample countries, in Table 4 we calculate the elasticity for each country using the formula described above. Sweden and Finland, followed by the Netherlands and Denmark are the sample countries yielding the highest elasticities, while on the other end, Greece presents the lower levels. In addition, as explained above, much higher elasticities appear in the case of labor productivity in comparison with both TFP measures.

Table 4. Average elasticities by country.

Country	Broadband >30 Mbps penetration 2021 (% firms)	Cloud penetration 2021 (% firms)	Elasticity – Increase in GVA (%) after 1% increase in cloud penetration	Elasticity – Increase in labor productivity (%) after 1% increase in cloud penetration	Elasticity – Increase in TFP-FE (%) after 1% increase in cloud penetration	Elasticity – Increase in TFP-OP (%) after 1% increase in cloud penetration
Austria	72.99%	43.51%	0.32%	0.30%	0.21%	0.17%
Belgium	89.45%	52.96%	0.40%	0.38%	0.26%	0.21%
Czech Republic	74.70%	43.75%	0.32%	0.30%	0.21%	0.17%
Denmark	94.96%	64.82%	0.50%	0.47%	0.32%	0.27%
Finland	80.22%	75.29%	0.56%	0.53%	0.36%	0.30%
Germany	84.83%	41.60%	0.31%	0.30%	0.20%	0.17%
Greece	60.82%	22.36%	0.16%	0.15%	0.10%	0.08%
Hungary	61.91%	29.37%	0.21%	0.19%	0.13%	0.11%
Ireland	78.01%	58.79%	0.44%	0.41%	0.28%	0.23%
Italy	78.35%	60.47%	0.45%	0.42%	0.29%	0.24%
Luxembourg	87.89%	33.48%	0.25%	0.24%	0.16%	0.13%
Netherlands	91.28%	64.94%	0.50%	0.47%	0.32%	0.26%
Norway	83.04%	64.02%	0.48%	0.45%	0.31%	0.25%
Poland	76.20%	32.39%	0.24%	0.22%	0.15%	0.13%
Portugal	89.68%	34.70%	0.27%	0.25%	0.17%	0.14%
Slovak Republic	68.57%	36.14%	0.26%	0.24%	0.17%	0.14%
Spain	88.37%	30.92%	0.24%	0.22%	0.15%	0.12%
Sweden	88.61%	75.39%	0.57%	0.54%	0.37%	0.30%
United Kingdom*	64.18%	53.03%	0.38%	0.35%	0.24%	0.20%

Note: *2020 data.
Source: authors' elaboration.

6.2. Analyzing the complementarity between BB and cloud

The model presented in section 4 assumes that broadband is complementary with cloud computing. This is justified since cloud computing needs broadband connectivity to deliver economic effects. From a microeconomic viewpoint, this should mean that cloud adoption may not only depend on its price, but also on the price of its complementary good, broadband.[17] In order to account for this peculiarity, we will replicate the baseline estimates but including broadband price as a driver of cloud adoption (Table 5).

Table 5. 3SLS fixed effects estimate – testing BB and Cloud complementarity.

Variables	[I]		[II]		[III]		[IV]	
Dependent variable	Log(GVA)		Log(GVA/L)		Log(TFP-FE)		Log(TFP-OP)	
Log(K)	0.4091***	(0.0245)						
Log(K/L)			0.4088***	(0.0237)				
Log(L)	0.5841***	(0.0396)						
Log(BB)	0.4219***	(0.1500)	0.4803***	(0.1225)	0.4169***	(0.1284)	0.6547***	(0.1265)
Log(BB)*Cloud	0.0018***	(0.0005)	0.0017***	(0.0004)	0.0011***	(0.0004)	0.0009**	(0.0004)
Dependent variable: Log(BB)								
Log(P_{BB})	−0.0605***	(0.0175)	−0.0519***	(0.0175)	−0.0508***	(0.0173)	−0.0525***	(0.0172)
Log(HK)	0.2263***	(0.0151)	0.2141***	(0.0153)	0.2099***	(0.0151)	0.2097***	(0.0151)
Log(VA per firm)	0.0213	(0.0181)	0.0402**	(0.0187)	0.0627***	(0.0183)	0.0498***	(0.0183)
R&D	0.0995***	(0.0257)	0.0994***	(0.0257)	0.0976***	(0.0253)	0.1020***	(0.0253)
Urban	−0.0153	(0.0361)	−0.0068	(0.0360)	−0.0073	(0.0355)	−0.005	(0.0355)
Dependent variable: Log(BB inv.)								
Log(P_{BB})	−0.1362***	(0.0364)	−0.1286***	(0.0363)	−0.0769**	(0.0364)	−0.1032***	(0.0364)
HHI	0.0001	(0.0003)	0.0001	(0.0003)	0.0001	(0.0003)	0.0001	(0.0003)
Dependent variable: Log(BB/L.BB)								
Log(BB inv.)	−0.0581***	(0.0157)	−0.1190***	(0.0197)	−0.1251***	(0.0197)	−0.1232***	(0.0196)
Dependent variable: Log(Cloud)								
Log(P_{CLOUD})	0.0159	(0.0252)	0.0193	(0.0254)	0.025	(0.0255)	0.0208	(0.0254)
Log(P_{BB})	−0.0748**	(0.0332)	−0.0746**	(0.0332)	−0.0871***	(0.0332)	−0.0794**	(0.0332)
Log(HK)	0.3366***	(0.0211)	0.3263***	(0.0213)	0.3232***	(0.0212)	0.3243***	(0.0213)
Log(VA per firm)	0.0259	(0.0245)	0.0316	(0.0252)	0.0500**	(0.0250)	0.036	(0.0251)
R&D	0.0775**	(0.0362)	0.0742**	(0.0365)	0.0729**	(0.0363)	0.0756**	(0.0364)
Urban	0.0574	(0.0516)	0.0583	(0.0516)	0.0558	(0.0515)	0.0585	(0.0516)
Dependent variable: Log(Cloud inv.)								
Log(P_{CLOUD})	−0.1270***	(0.0383)	−0.1165***	(0.0386)	−0.0883**	(0.0385)	−0.1094***	(0.0385)
Cloud companies	0.0132	(0.0807)	−0.0003	(0.0805)	−0.0082	(0.0804)	−0.0071	(0.0805)
Cloud zones	0.0196	(0.1222)	0.0349	(0.1220)	0.0275	(0.1219)	0.0305	(0.1221)
Dependent variable: Log(Cloud/L.Cloud)								
Log(Cloud inv.)	−0.023	(0.0176)	0.0092	(0.0289)	0.0003	(0.0288)	0.0068	(0.0288)
R-squared†	0.966		0.932		0.502		0.537	
Observations	517		517		517		517	

Note: *$p < 10\%$, **$p < 5\%$, ***$p < 1\%$. †Refers to first equation of the structural model. All equations in all estimates include country, year, and sector dummies.
Source: authors' elaboration.

The results are mostly similar as those in the baseline case. As expected, the coefficient associated to broadband price in the cloud adoption equation presents a negative and significant sign, a clear sign of product complementary. This means that an increase in broadband prices not only will reduce broadband adoption, but will also affect negatively cloud demand. Interestingly, cloud adoption seems to depend more critically on broadband price than on its own price, as this latest variable presents a non-significant parameter.

6.3. Heterogeneities by industrial sector

The next step is to conduct estimates differentiating cloud effects by economic sector (Table 6). These estimates are conducted based on the multi-equation model defined for the baseline model, although for brevity we only present here the results for the main equation.[18]

Table 6. 3SLS fixed effects estimate – effects by sector.

Variables	[I]		[II]		[III]		[IV]	
Dependent variable:	Log(GVA)		Log(GVA/L)		Log(TFP-FE)		Log(TFP-OP)	
Log(K)	0.4316***	(0.0246)						
Log(K/L)			0.4301***	(0.0238)				
Log(L)	0.5702***	(0.0393)						
Log(BB)	0.1808*	(0.1110)	0.1652	(0.1063)	−0.0533	(0.1106)	0.2328**	(0.1085)
Log(BB)*Cloud*Information and communication	0.0022***	(0.0004)	0.0023***	(0.0004)	0.0022***	(0.0005)	0.0017***	(0.0004)
Log(BB)*Cloud*Real estate	0.0010*	(0.0005)	0.0011**	(0.0005)	0.0009*	(0.0005)	0.0003	(0.0005)
Log(BB)*Cloud*Professional services	0.0006	(0.0005)	0.0006	(0.0005)	0.0009*	(0.0005)	0.0002	(0.0005)
Log(BB)*Cloud*Manufacturing	0.0020***	(0.0006)	0.0020***	(0.0006)	0.0020***	(0.0006)	0.0011*	(0.0006)
Log(BB)*Cloud*Construction	0.0017***	(0.0006)	0.0018***	(0.0006)	0.0021***	(0.0006)	0.0013**	(0.0006)
Log(BB)*Cloud*Transport and storage	0.0009	(0.0007)	0.0009	(0.0007)	0.0010	(0.0008)	0.0002	(0.0007)
Log(BB)*Cloud*Other services	0.0016***	(0.0006)	0.0017***	(0.0006)	0.0024***	(0.0006)	0.0010*	(0.0006)
R-squared†	0.970		0.942		0.574		0.636	
Observations	517		517		517		517	

Note: *$p < 10\%$, **$p < 5\%$, ***$p < 1\%$. †Refers to first equation of the structural model. All equations in all estimates include country, year, and sector dummies.
Source: authors' elaboration.

In most of the estimates, the largest coefficients for the interacted cloud variable are found for the case of information and communication, followed by manufacturing. As denoted by Oliveira et al. (2014), relative advantage, complexity, technology readiness, top management support, and firm size have a direct effect on the firm's adoption of cloud computing, something that is reflected on the fact that the manufacturing and services sectors have different drivers of cloud adoption. In this sense, the important economic effects derived from cloud on the manufacturing sector are consistent with Chen et al. (2022) findings for a sample of worldwide firms, where they concluded that manufacturing firms present a higher profitability from cloud than the service sector. The authors argue that manufacturing firms, as producers of tangible goods, are more capital intensive and tend to present more operative complexity, being then more prone to benefit from the positive effects derived from cloud computing (cost reductions, flexibility, and agility improvements).

In addition, the coefficient for other services (that include accommodation, food, and administrative services) also presents relevant coefficients, while on the other hand, professional services and transport are mostly insignificant. This points to a heterogeneous impact of cloud services on the economy, depending on the nature of each specific industry. Within the service sector, Liu et al. (2020) argue that firm's external environment significantly matters in cloud adoption and use patterns, something that may explain the uneven degree of impact between different service sectors.

However, the degree of economic impact attributable to each economic sector does not depend only on the coefficients, because as highlighted above, elasticities are a function also of current broadband and cloud penetration levels. In consequence, to find out which is the economic sector exhibiting the largest economic impact, we calculate the elasticities based on the average penetration levels by industry for both broadband and cloud (Table 7).

Table 7. Average elasticities by industry.

Industry	Broadband >30 Mbps penetration (% firms)	Cloud penetration (% firms)	Elasticity - Increase in GVA (%) after 1% increase in cloud penetration	Elasticity - Increase in labor productivity (%) after 1% increase in cloud penetration	Elasticity - Increase in TFP-FE (%) after 1% increase in cloud penetration	Elasticity - Increase in TFP-OP (%) after 1% increase in cloud penetration
Information and communication	92.94%	74.11%	0.74%	0.77%	0.74%	0.57%
Professional services	77.73%	38.31%	0.00%	0.00%	0.24%	0.00%
Real estate	82.60%	47.67%	0.21%	0.23%	0.19%	0.00%
Transport and storage	87.42%	58.56%	0.00%	0.00%	0.00%	0.00%
Manufacturing	78.61%	41.33%	0.36%	0.36%	0.36%	0.20%
Construction	73.00%	35.57%	0.26%	0.27%	0.32%	0.20%
Other services	84.52%	56.62%	0.27%	0.28%	0.40%	0.17%

Source: authors' elaboration.

As represented in Table 7, the results suggest that information and communication is the economic sector presenting the largest elasticities for all the four metrics considered, followed by manufacturing, in line with the expectations derived from previous studies (Chen et al., 2022). The larger impact on information and communication industry is consistent with the casual flows sketched in Figure 1, where this technology was described to be critical for industries intensive in IT inputs in general, and for software development in particular (Byrne et al., 2017).

7. Conclusions

The aim of this study was to investigate the economic effects derived from the adoption of cloud computing at the industry level. In order to do so, we developed an upgrade of the traditional multi-equation approach designed by Röller and Waverman (2001), and later improved by Koutroumpis (2009, 2019). This approach proved to be appropriate to endogenize both broadband and cloud adoption.

The proposed model was estimated for an industry-level sample of OECD countries. Our results suggest that, on average, an increase of 1% in cloud penetration will yield an increase in GVA of 0.33%, of 0.31% in labor productivity, and of 0.18–0.22% in TFP. In particular, the largest economic impact is seen, as expected, in the information and communication sector, followed by manufacturing. In contrast, no impact was detected for the professional activities and transport sectors.

In addition, our findings indicate important differences across economic sectors in their capacity to make the most of cloud technologies. A part of these disparities is explained as the economic impact of cloud computing depends on current levels of penetration of both broadband and cloud, therefore varying by country and industry. However, this is not the only explanation, as the coefficient associated with the cloud variable (interacted with broadband) in the production function was found to vary across economic sectors as well. Therefore, an area for future research will consist in understanding why these disparities emerge across sectors, and how lagging industries can make further steps to maximize the positive economic effects generated by the technology.

In addition, the analysis provided evidence about the positive and complementary nature between broadband and cloud computing. Broadband is a critical infrastructure for accessing the resources supplied by cloud computing: the large-scale benefits to cloud-adopting organizations can only be fulfilled in the context of high-speed broadband supply at affordable pricing. Therefore, broadband deployments remain critical to maximize this economic impact.

These findings can be interpreted as useful inputs for policymaking. Considering that cloud computing generates economic effects that go beyond the so-called ‘construction effect’ triggered by cloud computing providers’ investment in infrastructure (data centers, software, etc.), public policy can stimulate its development through several areas. Examples of such public actions can be identified in OECD (2014), including the following:

- Stimulate the adoption of cloud computing by removing some data localization regulatory barriers, raising awareness, developing skills and education, and establishing governments as lead users of cloud computing.
- Encourage and support the development and use of cloud computing interoperability standards, ensuring that they can be adapted to future needs and leave room for future innovation.
- Promote the development of complementary infrastructure. Especially in developing countries, some challenges are faced that prevent a widespread diffusion of cloud computing. This can be the case of limited electricity provision, and naturally, of broadband infrastructure in place providing a low-latency and robust internet connection to cloud users.
- Considering that cloud computing is one of the most advanced stages of networked computing, it is desirable to incentivize a thorough and holistic risk management approach to assure the availability, integrity, and confidentiality of data.

Finally, our study faced some limitations that are worth commenting. For instance, the sample of countries that report country and industry penetration figures for cloud computing is limited, which means that only a subset of OECD countries could be considered in this empirical exercise. As a result, given that our evidence is based on a sample of advanced economies, more research is needed in order to understand the dynamics of cloud computing in emerging regions. In addition, since the timeframe for our dataset is limited, it is not suited to measure economic growth models where medium and long-term cloud effects can be estimated. This means that future research will have to expand the time series to fill these gaps when more complete datasets become available.

Notes

1. Vu et al. (2020) provided empirical evidence of the relevance of broadband as a predictor of cloud computing adoption.
2. This analysis was conducted using the country’s input-output tables provided by Statistics Indonesia (AWS, 2021).

3. Koutroumpis (2009) also includes local loop unbundling as a metric associated to regulation, although he later discarded this variable in the latest version of his model (Koutroumpis, 2019).
4. These should not be confused with the direct effects generated by cloud revenue, nor by the direct, indirect, and induced effects derived from an initial investment in cloud (the so-called 'construction effect').
5. For instance, year-level fixed effects proved to be critical to absorb the COVID-related shock in our model during 2020.
6. More recently, Levinsohn and Petrin (2003) proposed instead an estimator using intermediate inputs as proxy for unobservable shocks affecting productivity. Levinsohn and Petrin (2003) argue that intermediate materials can be a better proxy for unobservable productivity shocks as they are expected to react more smoothly than investment, and because some firms may decide not to invest at all in some specific years. However, we were unable to estimate the approach recommended by Levinsohn and Petrin (2003) since, unfortunately, there is no data available on intermediate materials such as electricity or fuel consumed by industry level for the sample considered. In any case, as our sample is industry-aggregated rather than firm-specific, we believe that this theoretical advantages over the Olley and Pakes (1996) approach do not longer remain relevant.
7. We thank an anonymous referee for highlighting this.
8. The 19 countries included in the sample are detailed in Table 4. Sectors included: Construction; Information and communication; manufacturing; professional, scientific, and technical activities; real estate activities; transportation and storage; accommodation, food, and administrative services.
9. Using average exchange rates as reported by the International Monetary Fund
10. The reason to use 30 Mbps broadband is threefold. First, because the original definition for broadband based on 512 Kbps speed as reported by the ITU is completely outdated nowadays. Second, because in our sample, standard broadband penetration in fixed broadband is close to 95% of firms, thus indicating homogeneity in this kind of infrastructure. Third, because speed is a crucial variable associated to the economic impact derived from broadband.
11. When a single year of cloud penetration is missing between two reported values, we imputed the correspondent figure based on the compound average growth rate across that interval.
12. Weights for firms according to size were calculated based on the most recent OECD data, and given the lack of update in this indicator, were assumed to remain constant through the period.
13. The number of broadband lines per economic industry is calculated from the broadband penetration and the number of firms by sector within each country (source: OECD).
14. According to Oxford Economics, investment by public cloud service providers is measured through investment in the hardware infrastructure necessary to supply public cloud services (servers, storage, and ethernet switches).
15. To build the sectoral dummies, information and communication, and transportation and storage sectors are grouped into a single category named transport and communications. Similarly, accommodation, food, and administrative services are grouped in a category named other services.
16. These results are aligned with some found in previous studies that analyzed the effects of ICTs in TFP, although not focusing specifically on cloud computing. To cite an example, Ahmed (2017) found a positive contribution of ICT to TFP and TFP per unit of labor for a sample of ASEAN economies.
17. We would like to thank an anonymous referee for raising up this point.
18. Complete estimations are available for those who want to request them.

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