Telecom Advisory Services LLC

COMPARATIVE ASSESSMENT
OF ENERGY PRODUCTIVITY OF
CLOUD COMPUTING AND
INFORMATION TECHNOLOGY
IN EUROPE



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EXECUTIVE SUMMARY

The purpose of this study was to examine the contribution of cloud computing as a key component of the Information Technology (IT) industry in shaping energy consumption of European economies. The transformative power of IT in modern economies extends significantly into all economic sectors, including those most concerned with energy and environmental management. Accordingly, while the massive adoption of IT across individuals, governments, and enterprises can potentially drive a paradigm shift in energy consumption, it also offers a path to enhanced efficiencies. However, these advances are not without their potential drawbacks since the digital era also imposes a surge in energy demand. This is why it is necessary to conduct robust empirical analyses to identify the overall effect in aggregate energy implications of the migration to IT-intensive economies. In this context, this study is aimed to provide evidence that the energy consumed by cloud computing in particular, and the IT industry in general, while high, is more economically productive than that of other sectors (in other words, it produces more added value per unit of energy consumed). Along those lines, the European countries that foster the deployment of cloud computing data centers and accelerate their migration to an IT-intensive economy should be highly energy productive, which means that the energy consumed can have an additional impact on economic growth and consumer welfare.

The study focus is on a comparative assessment of energy productivity across sectors in Europe, measuring the gross value added gained from using a unit of energy. **The study's overarching conclusion is that cloud computing is highly energy productive, and that the IT sector is more energy-productive when compared with other sectors.** Additionally, the study measures the positive contribution of hyperscalers' data centers to energy productivity. Based on this evidence, cloud technology and IT industries can simultaneously fulfill two objectives: (i) contribute to a country's economic growth based on their well-documented externalities, while (ii) increasing the continent's overall energy productivity and, consequently, its competitiveness. The evidence generated by the study for Europe can be summarized as follows:

Energy productivity of a country's economy, measured as Gross Value Added² (GVA) by Megawatt hour of energy consumed, has been found to be positively associated with percent of public and private organizations migrating to cloud computing. An econometric model developed in this study regressing electricity productivity against cloud adoption and a series of controls among European countries indicates that 10% increase of cloud adoption will yield an increase in electricity

¹ As defined in the research literature, "energy productivity" measures the total economic value generated by energy consumed. It differs from the concept of "energy efficiency" which measures consumption of energy of plant and equipment. By measuring value produced, energy productivity includes energy efficiency as a denominator in its calculation, but it addresses how well an economy is doing. See IEA: Productivity: multiple benefits of energy efficiency. Retrieved in: https://www.iea.org/reports/multiple-benefits-of-energy-efficiency/productivity; and Rinker, M. (2019). "Energy metrics: Efficiency, productivity, and intensity", Journal of advanced manufacturing and processing. Retrieved in: https://aiche.onlinelibrary.wiley.com/doi/epd-f/10.1002/amp2.10032

² Gross Value Added is a key indicator in national accounts and is used to estimate how much industries contribute to the economy. It is also a proxy for Gross Domestic Product (GDP) in the output approach to measuring GDP.

productivity of 0.23% (a yearly increase equivalent to an average €8.6 per MWh consumed, or €1,088 million per country). This effect can be demonstrated with data of some specific European countries (Table A):

Table A: Economic gains in Energy Productivity yielded by an increase of 10% in cloud adoption

	Economic gains per MWh (euros) driven by a 10% increase in cloud adoption	Overall economic gains (million euros) driven by a 10% increase in cloud adoption
Austria	9.42 €	684.72 €
Belgium	9.37 €	821.38 €
Bulgaria	2.55 €	89.39 €
Croatia	5.20 €	86.15 €
Czech Republic	5.08 €	345.62 €
Denmark	15.86 €	533.69 €
Estonia	4.53 €	41.64 €
Finland	4.88 €	411.54 €
France	9.09 €	4,338.75 €
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Greece	6.02 €	336.80 €
Hungary	5.25 €	217.45 €
Iceland	1.77 €	32.65 €
Ireland	20.17 €	562.54 €
Italy	10.54 €	3,257.66 €
Latvia	6.91 €	48.50 €
Lithuania	6.57 €	77.20 €
Luxembourg	13.98 €	111.10 €
Netherlands	12.03 €	1,385.51 €
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Slovak Republic	5.67 €	161.13 €
Slovenia	5.36 €	77.59 €
Spain	8.58 €	2,175.66 €
Sweden	6.75 €	898.54 €
Switzerland	21.54 €	1,351.45 €
United Kingdom	15.92 €	5,193.05 €
Average	8.56 €	1,088.32 €

Source: Eurostat, IEA, Telecom Advisory Services analysis

The overall economic gains represent the increase in GDP for the country as a whole. Why do cloud service adoption drives an improvement of an entire country energy productivity? Because of the optimization in the supply of IT services. Energy productivity can increase further every year by promoting cloud penetration.

- On the other hand, energy productivity of a country's economy also depends on the supply of cloud services. An econometric model regressing cloud adoption, hyperscaler deployment and share of IT value added for a data panel of 38 European countries indicates that the deployment of each new availability zone³ will result in 0.2% increase of energy productivity (equivalent on average to € 833 million). This effect is driven by the implicit economies of scale in IT supply of large cloud service providers. In addition, cloud hyperscalers are expected to lead to greater energy productivity through advanced service optimization, which individual, traditional data centers are typically less prone to achieve.
- The high energy productivity of large cloud service providers manifests itself not only in the countries where they deploy infrastructure, but also in neighboring nations that host enterprises that purchase cloud services remotely. The nature of cloud infrastructure is such that data centers—located in strategic 'availability zones'—often serve multiple countries. These zones can comprise one or more hyperscaler data centers located in close proximity selected based on factors like suitable connectivity, electricity supply stability, and legal-economic environments, causing a spillover of efficiency that is expected to impact neighboring countries. Accordingly, an econometric model such as the one referred to above which incorporates neighboring country benefits of large cloud data centers demonstrates that, for example, a new availability zone being deployed in Italy, beyond the 0.2% increase in energy productivity locally (equivalent on average to €2.8 billion euros) will generate an increase of energy productivity of 0.05% in Greece by virtue of geographic spillovers (equivalent on average to €73 million euros).

To sum up, large cloud service providers are associated with higher energy productivity at two levels:

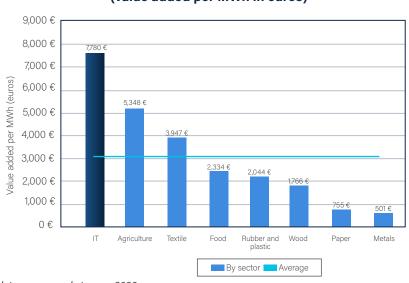
Deployment of a cloud zone by a large cloud service provider in country A

Increase in energy productivity of country A by 0.2%

Increase in energy productivity of country B adjacent to country A by 0.05%

³ An "availability zone" are geographies where a cloud service provider operates a data center. This should not be confused with the term "cloud regions" which may contain multiple "availability zones". While a availability zone may comprise multiple data centers, no two availability zones share the same data center. Therefore, each availability zone is self-contained and physically isolated from other availability zones in the same region to provide additional fault tolerance and resiliency.

Beyond the specific effect of cloud computing, energy productivity of the IT industry as a whole is much higher than that of other sectors. While the IT industry is often regarded as a heavy electricity consumption sector, it exhibits the highest energy productivity, when compared with other sectors in terms of GVA per unit of electricity consumed. On an average basis, the IT industry in European countries added € 7,780 per MWh in 2021 while agriculture added € 5,348 per MWh and food processing € 2,334 per MWh.



Graphic B. Europe: Average energy productivity by sector (2021) (value added per MWh in euros)

Note: Agriculture sector data corresponds to year 2020 Source: Eurostat, IEA, ITU, Data Center Map, Telecom Advisory Services analysis

In most European countries⁴ the IT sector is the most energy productive sector, while in few countries, it is ranked as the second most productive.⁵ For example, in France and Germany, the value added per MWh is close to twice that of agriculture (8,539.19 and 8,595.88 Euros per MWh, respectively).

Consequently, countries with a large IT sector and a strong presence of cloud service providers fulfill by far the highest value in energy productivity: considering the higher economic output per energy consumed for the IT sector, countries that exhibit higher share of value added for the IT sector, will display higher energy productivity. In general, one percentage point (e.g., from 4% to 5%) increase of IT as a percent of value added is associated with an increase in total energy productivity of 1%. Accordingly, and as also demonstrated by prior research, the massive adoption of IT across individuals, governments, and enterprises can potentially drive a paradigm shift in energy productivity. For instance, Ireland, a nation with an IT sector representing 19% of the country's value-added exhibits an average electricity productivity of 11,367.93 euros per MWh, more than three times that of Sweden, Germany and Poland, among others.

⁴ Austria, Belgium, Czechia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, and Sweden

⁵ Bulgaria, Poland, and Romania.

In terms of public policy implications of this evidence, promoting the development of information economies enabled by cloud computing will not only increase productivity in the aggregate (as it reduces costs) but will also contribute to a country's competitiveness, through higher energy productivity.

- Promoting the adoption of cloud computing services across firms and individuals will also increase energy productivity (as it reduces costs per value added) and contribute positively to the environment and ultimately state competitiveness.
- The presence of cross-national spatial spillovers suggests that countries can enjoy the benefits from large cloud infrastructure even if that is not being locally deployed, if they do not impose data localization regulations that prevent its full use.
- State development of the IT sector yields, in addition to the conventional competitiveness benefits, the environmental effect of added energy productivity.

1. INTRODUCTION

In the current era of unprecedented technological growth, energy efficiency and energy productivity have emerged as critical needs for achieving global sustainability combined with economic growth. Recent trends in global warming, have been raising concerns over environmental degradation, pushing the private sector and governments alike to examine their energy strategies, focusing on efficiency to mitigate climate change impact.

Consequently, in recent years, energy sustainability has turned into a proactive, innovative, and integral aspect of modern energy management. Factors such as technological innovation, economic considerations, and environmental awareness have been driving this shift. The aim of most governments to promote green agendas aiming for environmental sustainability underscores the need for efficient energy utilization, making it a central topic in public policy agendas. In Europe, the Energy Efficiency Directive, adopted in 2012 and subsequently updated in 2018 and 2023, sets rules and obligations for achieving the EU's ambitious energy efficiency targets.⁶

These objectives should be combined with economic growth as fostered by sectors that maximize value added per unit of energy consumed. Beyond energy efficiency, the concept of energy productivity is also a critical target. Since productivity measures the total economic value gained from using a unit of energy, this metric introduces an economic dimension to the public policy objective. By increasing the gross value added for the energy expended, an economy can foster growth. This is why it is necessary to conduct robust empirical analysis to identify the overall effect in aggregate energy sustainability of the migration to IT-intensive economies primary analytical focus of this research is to examine energy productivity by countries and sectors in Europe.

In this context, the objective of the study is to examine the role of the Information Technology (IT) industry, and more specifically of cloud computing and large cloud data centers, in shaping energy productivity. The transformative power of ICTs in modern economies extends significantly into all economic sectors, including those most concerned with energy and environmental management. The massive adoption of IT across individuals, governments, and enterprises results in an important increase in energy demand. However, it is relevant to examine the impact of this shift in energy productivity. This is why it is necessary to conduct robust empirical analysis to identify the overall effect in aggregate energy productivity of the migration to IT intensive economies. In this context, this study aims to provide evidence that the energy consumed by the IT industry and more particularly of large cloud service providers, while high, is more productive than that of other sectors, producing more added value per unit of energy consumed. If proven so, the countries that accelerate their migration to an IT intensive economy should be highly energy productive.

⁶ See https://energy.ec.europa.eu/topics/energy-efficiency/energy-efficiency-targets-directive-and-rules/energy-efficiency-directive_en

⁷ By measuring value produced, energy productivity includes energy efficiency as a denominator in its calculation, but it addresses how well an economy is doing (See IEA: Productivity: multiple benefits of energy efficiency. Retrieved in: https://www.iea.org/reports/multiple-benefits-of-energy-efficiency/productivity; and Rinker, M. (2019). "Energy metrics: Efficiency, productivity, and intensity", Journal of advanced manufacturing and processing. Retrieved in: https://aiche.onlinelibrary.wiley.com/doi/epd-f/10.1002/amp2.10032)

The study is structured in five chapters. In Chapter 2 we frame the hypotheses to be tested empirically in the study. They are supported by a review of the research literature included in appendix A. Chapter 3 presents the empirical specification and data to be used in several econometric models to test the causality between cloud computing service provisioning and energy productivity in Europe. Detailed review of the analyses is included in appendices B and C. Chapter 4 develops a descriptive analysis of energy productivity across European sectors, with the specific focus of comparing the IT sector with other industries. Data sources for the descriptive analysis are detailed in Appendix D. Finally, Chapter 5 presents the study conclusions and draws the policy implications.

2. STUDY THEORETICAL FRAMEWORK AND HYPOTHESES

Research on energy productivity, and the particular role of information technologies and data centers has been conducted for a number of years (see Appendix A. Review of the Research Literature). The principal objective of this study is to address a void in the research literature by examining the role of IT, and more specifically, of cloud computing, in making economies grow while increasing their energy productivity. In that sense, while recognizing that digital technologies are heavy energy consumers, **our purpose is to demonstrate that, when measured by value added per unit of electricity consumption, the energy productivity of the IT sector and large cloud computing service providers is higher than in other sectors.**

Along these lines, and based on the literature review, we put forward four study hypotheses:

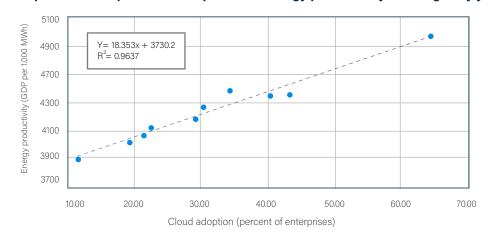
- The increase in cloud adoption by public and private organizations is a driver of state energy productivity.
- In particular, large cloud service providers, a key infrastructure of the information economy, are expected to be associated with higher energy productivity. Energy productivity of large cloud service providers manifest itself not only in the countries where they are deployed but also in neighboring nations that host enterprises that purchase cloud services. Hyperscalers, while being high energy consumers, can lead at the same time to greater energy productivity through economies of scale and advanced service optimization, not only within the countries they are located, but also in neighboring ones at a regional level.
- Moving to a more general level, in most countries the information technology (IT) industry depicts the highest energy productivity, when measured as Gross Value Added (GVA) per MWh. While recognizing the heavy energy consumption of the IT sector, its economic output per energy consumed is higher than that of other sectors.
- Consequently, countries with a large IT sector fulfill by far the largest values in energy productivity: considering the higher economic output per energy consumed for the IT sector, countries that exhibit higher share of GDP for the IT sector, will exhibit higher energy productivity.

These hypotheses will be tested with two methodologies:

- Econometric models analyzing the impact of cloud adoption, IT share of the economy, and cloud services supply with energy productivity.
- A descriptive analysis comparing economic output per energy consumed for different sectors, comparing the IT industry with other sectors in European countries.

3. ENERGY PRODUCTIVITY OF CLOUD COMPUTING

This chapter is dedicated to estimate the impact of energy productivity of cloud computing, as a technology infrastructure that is central to the IT sector (Appendix B presents the econometric model structure, and the descriptive data to be used in the models). Preliminary statistical evidence indicates a positive link between cloud computing and energy productivity, as plotted in Graphic 3-1: **European countries with higher cloud adoption are associated with a higher level of energy productivity** (measured as GDP per thousand MWh sold to non-residential end-users (million euros).



Graphic 3-1. Europe: Cloud adoption and energy productivity - averages by year

Source: International Energy Agency, Eurostat, OECD, Telecom Advisory Services analysis

The econometric strategy to be followed to gauge the causal link between both terms is threefold. First, we estimate the baseline empirical specification, through a simple fixed effects model. After that, we augment the baseline model into a spatial estimation to incorporate cross-national spillovers arising from cloud infrastructure (zones) being deployed in neighboring countries. Finally, we expand the model to account for dynamic effects in which current energy productivity is driven by its past values (Appendix D presents model results).

The baseline model regressing cloud adoption, hyperscaler deployment and share of IT value indicates that the deployment of an additional availability zone from a new service provider will result in an energy productivity increase of 0.2% (equivalent on average to €833 million euros). As indicated in all the models in Appendix C, when adding multiple controls to the econometric model as well as the time trend and year fixed effects, the impact of cloud adoption, and IT share remains significant.

Another aspect of the estimates presented in the cloud baseline model relates to the effect of availability zones on energy productivity of neighboring countries. Data centers operated by large cloud service providers are expected to lead to greater energy productivity through economies of scale and advanced optimization, which individual, traditional data centers are typically unable to achieve. The approach followed in the prior model ignored the spatial aspect related to availability zones that exists due to the geographical distribution of these infrastructures. The nature of cloud infrastructure is such that hyperscalers' data centers—located in strategic 'cloud regions'—often serve multiple countries. These locations are chosen based on factors like connectivity, electricity supply stability, and legal-economic environments, causing a spillover of efficiency that is expected to impact into neighboring countries. This interconnectedness requires a different analytical framework that transcends boundaries, recognizing the spatial relationships between observations. Therefore, we developed a spatial econometric model to understand the cross-country effects of availability zones on energy productivity This phenomenon is particularly relevant when countries share cloud infrastructure regions or are served by the same hyperscalers. A spatial econometric model allows the incorporation of these spatial spillover effects, providing a comprehensive understanding of cloud computing's regional impact.

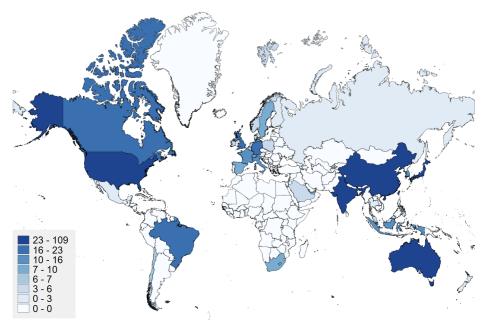


Figure 3-1. World distribution of Availability zones (2022)

Source: Telegeography, Telecom Advisory Services analysis

In Figure 3-1 we plot the world distribution of availability zones deployed by global service providers in cloud regions. Within this framework, countries adjacent to those hosting data centers may be benefiting from deployments in neighboring geographies. For example, most Latin American countries are expected to rely on the Brazilian cloud regions. Similarly, Saudi Arabia and the United Arab Emirates are expected to be supplying cloud services for neighboring MENA countries. Something similar occurs with China and India across Asian nations. In addition, South Africa appears to be the only African country with these infrastructures, thus expecting to serve most African economies. For this reason, we reformulate our baseline model to incorporate these cross-country spatial spillovers derived from the deployment of availability zones. This will consist in introducing as explanatory variable a new variable linking a country energy productivity with the deployment of availability zones across neighboring countries.

After building the spatial variable, we re-estimate the model. This effectively proves that a country being close to a availability zone but lacking cloud infrastructure will also derive energy productivity gains. In other words, the deployments of cloud hyperscalers are expected to generate positive effects in neighboring countries that are being served by that infrastructure. The quantification of the effect varies depending on each specific case, but we can provide a specific example to get a measure of the benefit a new availability zone being deployed in Italy will generate an increase of energy productivity of 0.05% in Greece (equivalent on average to €73 million euros).

In addition, the coefficients associated with the cloud adoption and IT share variables remain positive and significant, reinforcing the relevance of these indicators to explain disparities in energy productivity. Relying in the most conservative of these estimates, we can say that a 10% increase in cloud adoption will yield a 0. 23% increase in energy productivity (a yearly increase equivalent to €8.6 per MWh consumed, or €1,088 million for an average country). This effect can be demonstrated with data from some specific countries (Table 3-1):

Table 3-1 Economic gains in Energy Productivity yielded by an increase of 10% in cloud adoption

Country	Economic gains per MWh (euros) driven by a 10% increase in cloud adoption	Overall economic gains (million euros) driven by a 10% increase in cloud adoption
Austria	9.42 €	684.72 €
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Denmark	15.86 €	533.69 €
Estonia	4.53 €	41.64 €
Finland	4.88 €	411.54 €
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Ireland	20.17 €	562.54 €
Italy	10.54 €	3,257.66 €
Latvia	6.91 €	48.50 €
Lithuania	6.57 €	77.20 €
Luxembourg	13.98 €	111.10 €
Netherlands	12.03 €	1,385.51 €
Norway	5.53 €	688.38 €
Poland	5.51 €	875.69 €
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Sweden	6.75 €	898.54 €
Switzerland	21.54 €	1,351.45 €
United Kingdom	15.92 €	5,193.05 €
Average	8.56 €	1,088.32 €

Sources: Eurostat; International Energy Agency; Telecom Advisory Services analysis

Our results also indicate that if the weight of the IT sector in the economy increases in one percentage point (e.g., from 4% to 5%), energy productivity will increase in 1%.

Finally, we recognize that there is a **dynamic relationship between current and past values of energy productivity.** To address this possibility in our model, we replicate previous estimates but now including a lag of the dependent variable. In all cases, the dynamic effects are valid, as energy productivity seems to depend on its past values. More importantly for our purposes, the economic effect of cloud computing penetration seems to be unchanged after following this estimation strategy. To conclude, we tested several specifications of the econometric models in order to understand which is the most accurate.

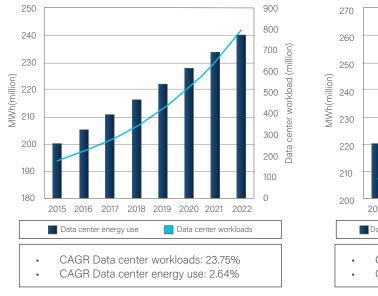
Our results are clear in pointing out that increases in cloud adoption are associated with improvements in energy productivity, thus reinforcing the critical role of cloud computing for development as identified in prior research. In addition, the share of the IT sector seems relevant to explain energy productivity in most of our estimates. Finally, we found that availability zones of large hyperscalers appear to matter as drivers of energy productivity. Our results have proven to be robust to the addition of country fixed effects, a large set of control variables, and temporal effects measured through different approaches (time-trend or year fixed effects). One of the main novel results is the evidence accounting for the existence of spillovers on neighboring countries derived from the deployment of cloud hyperscalers.

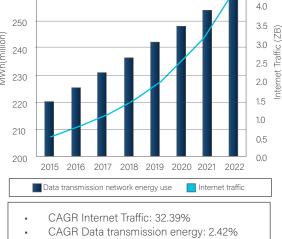
4. ENERGY PRODUCTIVITY OF THE INFORMATION TECHNOLOGY INDUSTRY IN EUROPE

The prior analysis confirmed the impact of cloud computing on energy productivity. Given the importance of this infrastructure within the IT industry, it is also relevant to investigate whether states that exhibit a higher share of their GDP related to IT industries also denote higher energy productivity. The objective of the following chapter is to generate evidence on the relationship between the IT industry and energy - primarily electricity - productivity and compare it with similar metrics of other sectors. For this purpose, we compiled data for agriculture, forestry, and fishing, and for some specific manufacturing industries, such as those related with food, textile, wood, paper, rubber and plastic, and metal products in European countries.⁸ For this analysis we built a dataset for European countries for 2021, considering that 2022 data is not yet consistently available across sources (see Appendix D for data sources for comparative analysis of energy productivity).

These datasets already allow drawing the first finding. While in the aggregate, the energy consumption in the IT sector is increasing rapidly, the rate of growth is slower than its output. As depicted in Graphic 4-1, internet traffic and datacenter workloads have been increasing at a much faster pace than the respective electricity consumption in each field. This is the result of the so-called Moore's law (Montevecchi et al, 2020), where diverse performance metrics in the digital field (such as processing power) usually evolve much faster than in traditional economic sectors.

Graphic 4-1. Europe: Evolution of global electricity consumption by IT component





5.0

4.5

Source: IEA, Telecom Advisory Services analysis

⁸ We excluded sectors that cannot be compared as their main source of energy is not electricity but fossil fuels (e.g., transport).

By applying the estimated average electricity consumption by exabyte and by data center to the data traffic and the number of data centers for each country, we obtain an estimate of electricity consumption by the IT sector in each segment. Internet traffic by country was obtained from the International Telecommunication Union (ITU). This data includes both mobile and fixed broadband. On the other hand, the number of data centers by country is reported in the Data Center Map database. Results for the calculation for electricity consumption in the IT industry is presented in Table 4-1.

Table 4-1. Europe: Calculation of electricity consumption for IT sector (2021)

IdDie 4-1. L	urope. Calcul	ation of electricity	Consumpt	ion for 11 sector	(2021)
Country	Internet traffic (exabytes)	Electricity consumption of internet traffic (MWh)	Number of Data Centers	Electricity consump- tion of Data Centers (MWh)	Electricity consumption of IT sector (MWh)
Austria	9.82	753,164.49	25	1,154,145.37	1,907,309.86
Belgium	14.47	1,109,787.00	40	1,846,632.03	2,956,419.03
Bulgaria	7.58	581,611.58	31	1,431,140.03	2,012,751.61
Czechia	12.76	978,298.00	24	1,107,978.66	2,086,276.67
Denmark	12.28	941,697.98	32	1,477,306.74	2,419,004.71
Finland	5.36	411,089.22	24	1,107,978.66	1,519,067.88
France	88.12	6,758,202.63	167	7,709,692.28	14,467,892.13
Germany	105.46	8,088,100.91	247	11,402,956.34	19,491,057.26
Greece	8.26	633,131.06	18	830,984.00	1,464,115.06
Hungary	7.92	607,200.49	9	415,492.00	1,022,692.48
Ireland	2.01	154,091.79	25	1,154,145.37	1,308,237.16
Italy	53.99	4,140,800.53	89	4,108,758.84	8,249,559.38
Latvia	3.18	243,891.86	18	830,984.00	1,074,875.86
Lithuania	2.92	224,230.73	12	553,989.33	778,220.07
Netherlands	20.47	1,570,090.14	122	5,632,229.51	7,202,319.65
Poland	27.42	2,103,090.57	41	1,892,798.74	3,995,889.31
Portugal	12.78	979,875.78	33	1,523,470.66	2,503,346.45
Romania	14.42	1,106,106.44	47	2,169,793.40	3,275,899.84
Slovakia	3.69	283,275.23	14	646,322.74	929,595.19
Sweden	13.08	1,003,398.02	62	2,862,280.07	3,865,678.09
United Kingdom	136.70	10,483,955.61	286	13,203,424.45	23,687,380.06

Sources: International Energy Agency; International Telecommunication Union; Data Center Map; Telecom Advisory Services analysis

⁹ https://www.itu.int/en/ITU-D/Statistics/Pages/publications/wtid.aspx

¹⁰ As fixed broadband traffic data was missing for Austria, France, Lithuania, Netherlands, Poland, and Sweden in 2021, we imputed estimates according to the number of fixed broadband subscriptions and the average traffic per subscription in the sample.

The values of electricity consumption for some of the countries in table 4-1 were validated with the figures estimated by Montevecchi et al. (2020) in their study submitted to the European Commission (see appendix D).

The aggregated results for energy productivity for all the economic sectors in European countries, calculated as the average by country (weighted by population), indicates that the IT industry stands out as the economic sector with the highest level of energy productivity.

9,000 € 8,000€ 7780 € 7,000 € Value added per MWh (euros) 6,000 € 5,348 € 5,000 € 4,000 € 3,000 € 2,000€ 1,000 € 0 € Agriculture Textile Paper Metals By sector Average

Graphic 4-2. Europe: Average energy productivity by sector (2021) (value added per MWh in euros)

Note: Agriculture sector data corresponds to year 2020 Source: Eurostat, IEA, ITU, Data Center Map, Telecom Advisory Services analysis

Beyond the aggregate estimates, the results by country are presented in Table 4-2.

Table 4-2. Europe: Energy productivity by economic sector (in euros) (2021)

Value added per MWh -2021 (euros)	Food	Textile	Wood	Paper	Rubber and plastic	Metals	Agriculture (*)	IΤ
Austria	3,186.63 €	2,814.96 €	1,899.92 €	447.59 €	2,237.78 €	1,056.97 €	3,407.49 €	7,494.85 €
Belgium	1,547.60 €	1,384.52 €	1,618.57 €	608.72 €	1,833.38 €	622.92 €	1,666.67 €	6,954.51 €
Bulgaria	1,146.26 €	1,904.69 €	502.70 €	459.87 €	813.36 €	401.88 €	5,625.74 €	2,339.77 €
Czechia	2,225.13 €	1,728.59 €	2,411.28 €	564.19 €	1,920.04 €	380.10 €	4,238.13 €	7,178.05 €
Denmark (*)	1,761.53 €	4,148.55 €	2,896.12 €	2,146.89 €	2,145.21 €	782.96 €	2,381.55 €	5,999.24 €
Finland	1,318.01 €	4,177.54 €	1,354.96 €	208.03 €	1,453.70 €	257.85 €	4,165.95 €	9,256.92 €
France	1,923.65 €	4,297.50 €	1,743.39 €	711.44 €	1,463.53 €	346.68 €	4,531.22 €	8,539.19 €
Germany	2,693.96 €	4,099.46 €	1,976.00 €	567.80 €	2,388.89 €	508.46 €	4,834.04 €	8,595.88 €
Greece	3,158.40 €	1,778.93 €	1,107.56 €	1,099.77 €	479.00 €	259.20 €	2,819.47 €	4,033.26 €
Hungary	913.80 €	2,120.63 €	831.70 €	706.65 €	959.82 €	673.30 €	4,565.20 €	6,865.46 €
Ireland	7,482.03 €	4,430.68 €	1,758.53 €	6,496.66 €	3,520.27 €	2,961.43 €	6,366.93 €	57,926.91 €
Italy	2,154.23 €	5,035.38 €	1,335.47 €	700.04 €	1,584.58 €	540.02 €	5,286.47 €	7,484.09 €
Latvia	2,016.61 €	5,491.78 €	1,378.87 €	3,227.87 €	3,486.08 €	1,161.63 €	6,135.23 €	1,688.55 €
Lithuania	2,000.10 €	3,180.73 €	1,702.85 €	1,317.17 €	1,575.68 €	1,118.00 €	8,822.20 €	2,758.19 €
Netherlands	2,715.61 €	3,156.69 €	3,795.21 €	1,114.96 €	1,957.50 €	608.99 €	1,180.89 €	5,709.51 €
Poland	1,814.26 €	5,057.96 €	1,697.48 €	826.72 €	1,968.25 €	374.00 €	7,317.92 €	6,145.27 €
Portugal	1,966.19 €	3,637.75 €	1,401.33 €	368.58 €	8,488.49 €	431.76 €	4,101.67 €	3,396.87 €
Romania	4,197.80 €	4,724.33 €	1,579.94 €	828.19 €	3,350.54 €	347.28 €	17,168.43 €	4,742.39 €
Slovakia	2,849.57 €	6,214.95 €	3,123.81 €	385.39 €	1,714.86 €	402.20 €	6,492.40 €	4,924.68 €
Sweden	2,099.66 €	2,385.40 €	2,582.46 €	257.61 €	1,711.54 €	517.43 €	6,020.34 €	10,680.89 €
United Kingdom	3,383.97 €	2,843.98 €		468.00 €		755.99 €	3,887.97 €	6,444.86 €

Country where the IT sector is the most energy efficient

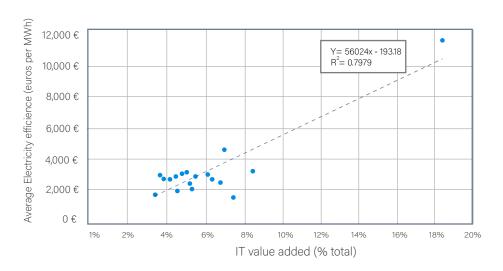
Country where the IT sector is the second most energy efficient

Note: (*) data for Agriculture sector and for Denmark (excepting IT) corresponds to year 2020. It is not possible to calculate values for other sectors beyond IT and agriculture in the United Kingdom because data on electricity consumption is not available in Eurostat.

Source: Eurostat, IEA, ITU, Data Center Map, Telecom Advisory Services analysis

As depicted in Table 4-2, in most European countries the IT industry is the one with the highest energy productivity. It is remarkable the position of Ireland, a country with a very strong IT sector and presence of several multinational big technology companies, reaching by far the largest value in energy productivity for the IT industry. On the other hand, in Bulgaria, Poland, and Romania IT is the second sector with the highest energy productivity. In Lithuania and Slovakia, IT comes third after agriculture and textile manufacturing, while in Portugal, IT reaches the fourth place after rubber and plastic manufacturing, agriculture, and textile manufacturing. Only in Latvia the IT sector occupies a low position.

If we consider the average energy productivity by economic sector along with the share of the IT industry on the economy, we can conclude that on average, **a higher weight of IT in the economy (as share of GDP) is associated with higher energy productivity** as denoted in Graphic 4-3.



Graphic 4-3. IT sector share and average energy productivity (euros per MWh)

Source: Eurostat, IEA, ITU, Data Center Map, Telecom Advisory Services analysis

All this evidence seems to suggest that the IT sector is among the leaders in terms of energy productivity, and that a larger share of this industry in the economy seems to be associated with higher energy productivity overall. This descriptive evidence will be complemented with the econometric analyses to be present below and supported by models in Appendix C.

In sum, countries with a large IT sector and a strong presence of cloud service providers fulfill by far the highest value in energy productivity: considering the higher economic output per energy consumed for the IT sector, countries that exhibit higher share of value added for the IT sector, will display higher energy productivity. In general, one percentage point (e.g., from 4% to 5%) increase of IT as a percent of value added is associated with an increase in total energy productivity of 1%. Accordingly, and as also demonstrated by prior research, the massive adoption of IT across individuals, governments, and enterprises can potentially drive a paradigm shift in energy productivity. For instance, Ireland, a nation with an IT sector representing 19% of the country's value-added exhibits an average electricity productivity of 11,367.93 €euros per MWh, more than three times that of Sweden, Germany and Poland, among others.

5. CONCLUSION

The aim of this research was to provide evidence on the relevance of the IT sector in general and cloud computing with regards to energy productivity.

As mentioned in the first study hypothesis, cloud computing large data centers are expected to be associated with higher energy productivity. We developed an empirical specification based on the main drivers of energy productivity and estimated it empirically through different approaches. As a particular specification, we introduced spatial effects where deployments in cloud infrastructures in a country are expected to drive cross-national spillovers to its neighboring economies that will benefit from those infrastructures. Our results are clear in pointing out that increases in cloud adoption are associated with improvements in energy productivity, thus reinforcing the critical role of cloud computing for development as identified in existing research. We also provided important evidence accounting for the existence of cross-country spillovers derived from the deployment of cloud hyperscalers, thereby providing evidence in support of the second hypothesis.

The descriptive analysis provided evidence in support of the third hypothesis. In most countries the information technology (IT) industry depicts the highest energy productivity, when measured as GVA per MWh. While recognizing the heavy electricity consumption of the IT sector, its economic output per energy consumed is higher than that of other sectors. In most European countries, the IT industry exhibits the highest energy productivity, when compared with other sectors in terms of GVA per unit of electricity consumed. In fact, while the IT industry is often regarded as a heavy energy consuming sector, its economic output per energy consumed in Europe is much higher than that of other sectors.

Consequently, as articulated in the fourth hypothesis, countries with a large IT sector fulfill by far the largest values in energy productivity: considering the higher economy output per energy consumed for the IT sector, countries that exhibit higher share of GDP for the IT sector, will exhibit higher energy productivity. The most prominent example of this case is Ireland a country with a very strong IT sector and presence of several multinational big tech companies. Across European countries, a higher weight of IT in the economy (as share of GDP) is associated with higher energy productivity.

The industrial policy implications of this evidence are clear. First, promoting the adoption of cloud computing services across firms and individuals will increase energy productivity (as it reduces costs) and will also contribute positively to competitiveness, through higher energy productivity. Second, the presence of cross-national spatial spillovers suggests that countries can enjoy the benefits from cloud investments despite not being locally deployed, thus meaning that data localization regulations that prevent full use of infrastructure adjacent to the countries hosting a availability zone may limit the full contribution of energy productivity of large-scale cloud service providers.

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APPENDIX A. REVIEW OF THE RESEARCH LITERATURE

A.1. Energy efficiency, energy productivity and their drivers

In line with most public policy agendas worldwide that are increasing their efforts towards sustainable economic growth, energy efficiency and energy productivity have been raised as an important concern in the research literature. For example, the study by Atalla and Bean (2017) focused on the analysis of the determinants of energy productivity, defined as the ratio of economic output per unit of energy consumed. Using a database of 39 countries for the period 1995-2009, the authors employ various analytical techniques to identify the determinants of energy productivity. One key insight drawn from this analysis is that most country-level increases in energy productivity were found to take place due to improvements within sectors rather than shifts in economic structure. In addition, the authors found that the highest rate of improvement in energy productivity was registered in former communist countries that have been undergoing economic liberalization processes through that period. Their results also point to income per capita and energy prices as drivers of energy productivity, while a greater share of output from industry was found to be associated with lower energy productivity levels.

Coinciding partially with some of the conclusion of the prior study, Sineviciene et al. (2017) analyzed the drivers of energy efficiency during the period 1996–2013 in Eastern Europe post-communist economies. Relying on a stochastic frontier function approach and a comparative analysis to examine long-run dynamic relations, the authors point to GDP growth as a key factor increasing both energy efficiency, while fixed capital formation and the share of industry in the economy are also important drivers. In short, changes in industry structure also appear to play a role in driving improved energy efficiency. This is partially consistent with the research of Chang and Hu (2010), who developed a total-factor energy productivity index to evaluate the change in regions in China. They found that factors affecting energy efficiency are linked to economic development, to the electricity share of energy consumption, coupled with the sector structure of the economy. While this study focuses energy consumption and efficiency rather than energy productivity, by relating these to level of development and the share of different sectors of the economy, it provides an analytical framework of causality that is useful to understand energy productivity.

Turning to an additional perspective, Uwasu et al. (2012) explored the drivers of energy productivity, defined as the ratio of Gross Regional Product and energy input, in China's provinces during the period between 2004 and 2007. The authors disaggregated energy productivity into two attributes: technology use and input factors. On this basis, they estimated energy technology levels, with results showing that disparities exist across the provinces even after controlling for differences in the contribution of input factors to energy productivity, implying **the importance of technological advancements for energy productivity enhancement**. They also argue that investment in technology and the quality of capital can indirectly determine the level of energy productivity.

Song and Zheng (2012) conducted an econometric study using a Chinese provinciallevel panel data set for the period between 1995 and 2009, concluding that **while increasing incomes were a substantial factor in driving energy efficiency, energy prices were not a key driver**. They also noted that the growth in urbanization rates presented obstacles to enhancing energy intensity.

In another study covering four decades and examining 75 nations, with a special focus on Latin America, Jimenez and Mercado (2014) analyzed energy intensity trends. Their research revealed that **advancements in energy efficiency were mainly due to improvements in energy intensity**¹ **across the economy**. Their econometric evaluation identified that critical factors included rising per capita income, oil prices, and overall economic expansion.

To sum up, the research literature has identified so far, several drivers of energy productivity and efficiency that will be taken into consideration in our empirical work (see table A-1).

Table A-1. General economic drivers of energy productivity and efficiency

Drivers	Research literature
GDP / Income per capita	Atalla and Bean, 2017
	Sineviciene et al., 2017
	Song and Zheng, 2012
	 Jimenez and Mercado, 2014
	Chang and Hu, 2010
Sectoral structure of the	Atalla and Bean, 2017
economy	Sineviciene et al., 2017
	Chang and Hu, 2010
Fixed capital formation	Atalla and Bean, 2017
	Sineviciene et al., 2017
Capital quality	• Uwasu et al., 2012
Productivity	• Uwasu et al., 2012
Energy prices	Atalla and Bean, 2017
	 Jimenez and Mercado, 2014
Technological advances	• Uwasu et al., 2012
Urbanization	Atalla and Bean, 2017
	Song and Zheng, 2012

A.2. Energy productivity and efficiency in the ICT sector

The specific role of ICT in driving energy productivity and efficiency has been less researched than general drivers, although the existing evidence provides some important insights regarding the **impact of digital technology**.

Berkhout and Hertin (2001) identified five domains where ICTs could enhance production efficiency, consequently lowering energy use: (i) Intelligent production processes; (ii) Intelligent creation and operation of goods and services; (iii) Intelligent distribution and logistics, such as enhancing supply chain efficacy or modifying distribution frameworks; (iv) Transforming consumer-producer

¹ Energy intensity is defined as the ratio of the total final consumption of energy and the GDP, thereby closer to the term of energy productivity used in this study.

dynamics through, for instance, mass customization; (v) Restructuring of work organization, like the adoption of remote work practices. In a similar conclusion, Sui and Rejeski (2002) have characterized the positive environmental impact of ICT as the "three D's for the new economy": the transition from physical to digital formats (they call it dematerialization), the move towards a less energy-demanding economy (decarbonization), and reduced necessity for physical movement due to digital alternatives (demobilization). Further, Beier et al. (2018) argued that the adoption of the Internet of Things (IoT) in industries can pave the way for more resource-conservative production, enhanced recycling methodologies, and anticipatory maintenance routines. In addition, some authors have argued that smart energy consumption feedback systems, supported by a range of digital technologies, have the capability to drastically diminish energy requirements within residential areas (Buchanan et al, 2015; Jensen et al, 2016; Malmodin and Coroama, 2016; Nilsson et al, 2018).

Other authors present a more nuanced view of the positive impact of ICT on energy efficiency. For example, Lange et al. (2020) examined four primary effects linking ICT deployment and energy efficiency: (i) the direct energy consumption stemming from ICT production and usage, (ii) the potential energy efficiency gains due to digitalization, (iii) the economic growth spurred by enhanced productivity, and (iv) the shift towards a more service-oriented economy with the proliferation of ICT services. The authors main conclusion is that while certain aspects of digitization promote energy efficiency, these are overshadowed by the increased energy demands brought about directly by ICT and indirectly through economic growth stimulated by digitization. Consistently with this conclusion, Batool et al. (2022) explore the relationship between ICT and energy consumption across various sectors in China. Their research uses a threshold regression analysis, considering ICT as a critical point influencing energy consumption behavior within residential, industrial, and transport sectors for the period 1990-2021. The study unveiled an asymmetric impact of ICT on energy consumption, with varying outcomes across different sectors. One of the authors' critical insights is the potential for ICT to generate rebound effects² — situations where increased efficiency leads to more energy consumption due to behavioral or systemic responses. However, there are a number of studies and simulations that indicate that, when considered in the aggregate, the rebound effects are too small in relation to the efficiency effects.3

A.3. Energy efficiency, energy productivity, and cloud computing

In recent years, cloud computing has emerged as a transformative force, reshaping how businesses operate and how services are delivered. Massive investments have

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² The term rebound is used to describe effects which prevent the potential savings resulting from efficiency increases from being realized (at all or in full). It is measured as the percentage of the theoretical savings potential of efficiency increases which cannot be saved due to consumer behavior. Direct rebound results in an increased demand for the same good due to, for example, lower prices. Indirect rebound measures increased demand for other goods driving energy consumption as a result of savings in consumption of primary good.

³ See Gillingham, K., M. Kotchen, D. Rapson, G. Wagner, 2013. "The Rebound Effect is Over-played." *Nature*, 493: 475-476. http://www.nature.com/nature/journal/v493/n7433/full/493475a.html In an opposite view, see Brockway and Sorrell (2016).

been conducted recently by global players such as Alibaba, Amazon Web Services, Microsoft, or Google in cloud platforms across the globe, while the share of firms and individuals that purchase cloud services has been increasing steadily through the years. This situation has brought the need to explore the potential of cloud computing not just as a technological innovation but also as a potential tool for energy productivity and efficiency.

The theoretical contribution of cloud computing to energy efficiency lies in the optimized utilization of computing resources and the agility in adopting efficient software solutions. Traditional data centers are known for their high energy consumption, primarily due to underutilization of resources and the need for constant cooling systems (Mastelic and Brandic, 2015). Cloud computing, with its shared resources model, optimizes the use of hardware, thereby increasing the workload per energy unit consumed. This principle allows for significant energy savings compared to traditional computing methods (Fiandrino et al.., 2017). Along these lines, the cloud computing shared resources model optimizes the use of hardware, increasing the workload per energy unit consumed. Similarly, another study estimates a technical savings potential of 87% in energy consumption if typical office applications are shifted to the cloud.⁴

Moreover, cloud data centers benefit from economies of scale. Large-scale operations allow for more significant investments in energy-saving technologies, such as advanced cooling systems, renewable energy sources, and state-of-the-art server technology, which smaller data centers might not afford (Vashist and Singh, 2013). The deployment of large cloud hyperscalers contribute to maximize the benefits of economies of scale. For example, research evidence indicates that while hyperscalers are heavy energy consumers, research commissioned by AWS shows that that their infrastructure is 3.6 times more energy efficient than the median of the surveyed US enterprise data centers. Consequently, companies that have migrated to the cloud are expected to report not only reduced operational costs but also decreased energy usage. These savings are most notable in organizations with fluctuating demands, as cloud computing allows them to scale resources up or down based on real-time needs, avoiding the inefficiencies of unused resources.

Despite its potential, achieving energy efficiency through cloud computing is not without challenges. Data centers' energy efficiency varies significantly based on their design, usage, and geographical location. The reliance on renewable energy sources and the effectiveness of cooling technologies are also important factors (Mastelic and Brandic, 2015). Furthermore, the rebound effect discussed above might suggest that the cost savings and efficiencies gained from cloud computing could lead to increased consumption, potentially mitigating some of the environmental benefits. That said, no research has been conducted to date to document the potential impact of rebound effects in cloud computing.

⁴ Masanet, E., Shehabi, A., Ramakrishnan, L., Liang, J., Ma, X., Walker, B., Mantha, P. (2014). *The Energy-efficiency Potential of Cloud-Based Software: A US Case Study*. Berkeley, CA: Lawrence Berkeley National Laboratory.

⁵ 451 Research (2019). The Carbon Reduction Opportunity of Moving to Amazon Web Services

APPENDIX B. ECONOMETRIC MODELS STRUCTURE AND DESCRIPTIVE DATA

B.1. Econometric model

The empirical specification to be estimated for cloud computing is presented in the following equation, where i and t denote respectively country and year:

```
log(Energy productivity<sub>it</sub>)
= \alpha_i + \beta \log(\text{Cloud}_{it}) + \delta \text{ Availability zones}_{it} + \varphi \text{ IT share}_{it} + \lambda X_{it} + \gamma_t + \varepsilon_{it}
```

The dependent variable is energy productivity, which is expected to depend on a country-level fixed effect (α_i) , on cloud adoption, on the number of zones being deployed by global cloud service providers across regions, and on the weight of the IT sector in the economy.

The diversity of ICT-related variables aims to address the complexities in the link between digital technologies and energy productivity as described in the literature review. Cloud computing, characterized by on-demand availability, resource pooling, and rapid elasticity, has changed how computing resources are accessed and used. From that perspective, we expect a higher cloud adoption rate across the economy to yield larger energy productivity, although the rebound effect can potentially mitigate or even counteract those positive results, as highlighted in the literature review. In addition, the relevance of cloud computing is not only driven by firms demanding these services, but critically on the supply side as well, as availability zones, managed by large scale cloud service providers, are high energy consumers but at the same time can lead to greater energy efficiency through economies of scale and advanced optimizations, which individual, traditional data centers are typically unable to achieve. Finally, the inclusion of the share of IT sector in the economy aims to control for potential effects related to this industry beyond cloud adoption or its infrastructure deployments.⁶

The inclusion of country fixed effects is especially relevant to control for time-invariant factors that may make some economies more productive in their energy use because of unobserved characteristics. The term X represents a vector of time-varying control variables that could be associated to different levels of energy productivity, as identified in the literature review above (see section 2.1). Finally, γ_t captures temporal effects affecting all the sample, and ε_{it} is the error term. Controlling for temporal effects is also relevant, as it may account for exogenous technological change if it affects all the countries included in the sample.

B.2. Descriptive data to be used in the models

An unbalanced panel was compiled for 38 countries covering the period 2013-2020. Data availability prevented us from expanding the sample for more economies, as

⁶ We also considered including broadband penetration as an additional regressor. However, the coefficient associated to this variable was very far from being significant across all the model specifications, so it was finally discarded.

we were restricted by the countries reported in OECD Stat⁷ and Eurostat. The time dimension of the panel was also constrained, as data on cloud adoption is mostly unavailable before 2013, while 2020 is the last year of real electricity consumption data reported by the IEA. The economies included in our sample are listed in Table B-1.

Table B-1. Countries included in the sample for the econometric analysis

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

Source: Telecom Advisory Services analysis

In Table B-2 we present the set of variables to be used in the empirical analysis. The dependent variable is energy productivity, defined as GVA by TWh of electricity consumed. GVA data was obtained from Eurostat, while electricity consumption was extracted from the IEA database. The values for this (and all variables to be represented in monetary units) were deflated and expressed in 2015 constant prices, to remove the effects of inflation.

As for the IT related variables, cloud adoption is defined as the share of firms purchasing cloud computing services (data compiled from OECD Stat).⁸ In addition, to account for investment in local cloud infrastructure, we included the number of zones in cloud regions being deployed by global cloud service providers, information provided by TeleGeography.⁹ The weight of the IT sector (calculated as the share of its GVA across the whole economy) is obtained from Eurostat.

⁸ 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.

⁷ https://stats.oecd.org

⁹ TeleGeography provides a list of cloud regions being deployed since 2006 that were used to build the stock of availability zones. Global providers contemplated in the database are Alibaba, Amazon Web Services, Microsoft Azure, Google Cloud Platform, IBM Cloud, Oracle Cloud, OVH, and Tencent Cloud. Cases where the launching date was not available in the dataset were excluded.

Table B-2. Variables description and main statistics

Variable	Description	Source	Mean	Std. dev.
Energy productivity	Gross value added per TWh of electricity consumed (million US\$ at 2015 constant prices)	Eurostat / IEA	4226.801	2182.680
Cloud	Businesses purchasing cloud computing services (%)	OECD	0.289	0.167
Availability zones	Number of zones in cloud regions	TeleGeography	3.572	10.650
IT share	Gross value added for information and communication sector (% of total GVA)	Eurostat	0.049	0.019
Manufacturing share	Gross value added for manufacturing sector (% of total GVA)	Eurostat	0.159	0.059
Agriculture share	Gross value added for agriculture, forestry, and fishing sector (% of total GVA)	Eurostat	0.028	0.018
GDP pc	GDP per capita (US\$ at 2015 constant prices)	World Bank	34640.730	22885.330
Capital formation	Gross fixed capital formation (% of GDP)	World Bank	0.219	0.044
Urban	Urban population (% of total population)	World Bank	0.767	0.118
TFP	TFP at constant national prices (2017=1)	Penn World Tables / World Bank	0.992	0.029
FDI	Foreign direct investment, net inflows (% of GDP)	World Bank	0.041	0.193
Electricity cost	Price of electricity (US\$ cents per kWh at 2015 constant prices)	World Bank	15.195	5.317

Source: Telecom Advisory Services analysis

As for the control variables, it is important to consider an extensive set of time-varying potential drivers of energy productivity in order to correctly isolate the cloud computing variables. First, we first must control for the sectoral structure of the economy because the different economic sectors vary in terms of their energy consumption. Therefore, we include the weight of the manufacturing sector in the economy, as suggested by related research (Atalla and Bean, 2017; Sineviciene et al, 2017). We also include the share of agriculture activity. As a result, we are effectively controlling for sectoral structure of the economy by accounting for the weight of manufacturing, agriculture, and IT sector, leaving the remaining services as a baseline scenario.

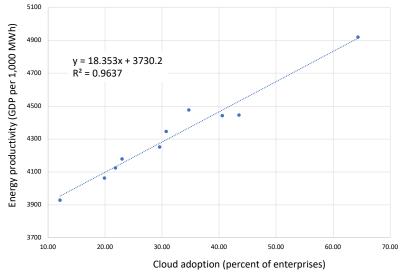
We also incorporate average income levels (measured through GDP per capita) as a driver of energy productivity, as has been highlighted by most of the specialized literature (Atalla and Bean, 2017; Chang and Hu, 2010; Jimenez and Mercado, 2014; Sineviciene et al, 2017; Song and Zheng, 2012). This indicator is expected to capture the effects associated to variations in income, as well as other factors linked to economic development not captured by the country fixed effects. The data was compiled from the World Bank database.

Investment in capital has also been identified as a potential driver of energy productivity (Atalla and Bean, 2017; Sineviciene et al, 2017). Economies with high investment intensity should replace their capital stock faster, therefore being expected to have on average newer energy-productive capital (Atalla and Bean, 2017). We control for this factor by including the share of gross fixed capital formation in the GDP (data source: World Bank).

In addition, Uwasu et al (2012) argues that the quality of capital matters as well, proposing Foreign Direct Investment (FDI) as a measure to control for this. Therefore, we control for FDI net inflows as a share of GDP, data provided by the World Bank. Total Factor Productivity (TFP) is also an important part of energy productivity according to Uwasu et al. (2012). Thus, we compiled this indicator from the Penn World Tables (PWT) as a further control. As the latest PWT database available covers up to 2019, to estimate the value of TFP during 2020 by assuming that it evolved at the same growth rate as labor productivity.

Urbanization is also expected to be a relevant driver of energy efficiency, as argued by Atalla and Bean (2017). As highlighted by the authors, moving from rural areas to urban and industrialized economies will likely stimulate more energy intensive activities, although is equally true that urban areas are expected to present more energy productive sectors like financial services. Without having a clear picture on the overall effect, we introduced the share of population living in urban areas (data from World Bank) as an additional control. Finally, we also included as a control the price of electricity provided by the World Bank (US\$ cents per kWh). As argued by Atalla and Bean (2017), energy prices are usually an important component of production costs, with higher prices being expected to lead to lower energy consumption and to shift the development and adoption of less energy intensive capital.

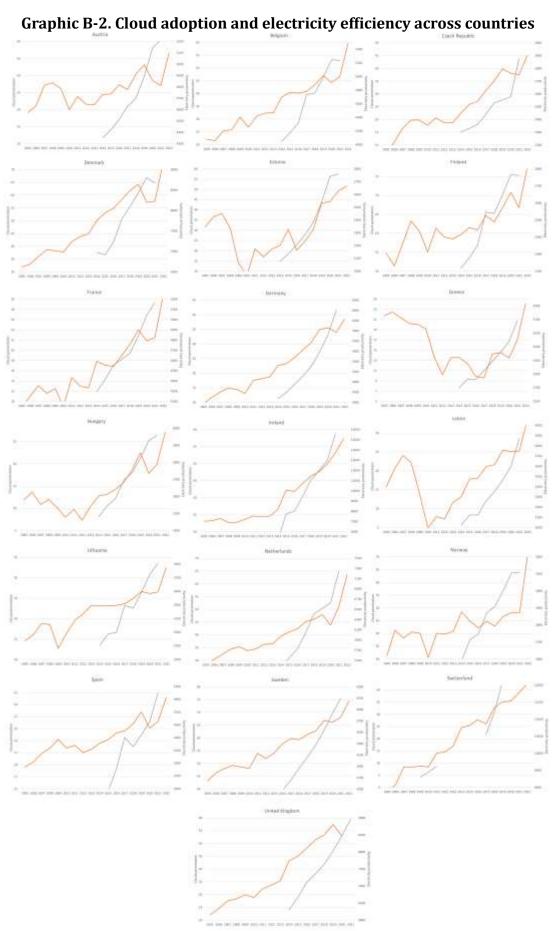
In order to get some preliminary insights related to cloud computing and energy productivity, we plot both variables using year averages for both cloud adoption and electricity efficiency, with results showing an almost perfect fit for a linear relationship.



Graphic B-1. Cloud adoption and energy productivity - averages by year

Source: IEA, Eurostat, OECD, Telecom Advisory Services analysis

In order to get a complementary view at a country-level, we present in Graphic B-2 the evolution across the years in both cloud adoption and electricity efficiency for selected countries. The series of electricity efficiency can be backwardly extended to 2005, since there is data available that allow us to understand previous patters. The evidence points to a clear positive link between both variables.



Source: IEA, Eurostat, OECD Stat, Telecom Advisory Services analysis

APPENDIX C. ECONOMETRIC MODEL RESULTS

C.1 Baseline Availability zone Model

The results for the econometric estimations developed in the baseline models are presented in Table C-1. All estimates were developed through panel data fixed effects models with robust standard errors clustered by country.

Table C-1. Baseline Cloud Model: Fixed Effects estimation of energy productivity drivers

•			4	
Dep. var.: log (Energy productivity)				` ,
Log (Cloud)	0.077***	0.053***	0.031**	0.030**
Log (Gloud)	[0.013]	[0.018]	[0.013]	[0.014]
Availability zones	0.077*** 0.053*** 0.031* [0.013] [0.018] [0.013] 0.002** 0.003*** 0.002 [0.001] [0.001] [0.001] 2.892*** 1.546*** 1.482* [0.469] [0.440] [0.456] 0.499 0.552 [0.366] [0.367] -0.914 -1.08 [0.936] -0.93 0.355*** 0.260* -0.12 0.039] [0.039] [0.036] -0.191 -0.93* -0.93* [0.595] [0.688] 0.006 0.075* [0.194] [0.167* -0.004 -0.004 -0.004 -0.004 -0.004 -0.004 [0.003] -0.011 -0.003 -0.011 -0.003 0.008 [0.004 -0.004 0.008 [0.004 -0.004 0.008 [0.004 -0.004 0.008 [0.004 -0.004 0.008 [0.004 -0.004 0.008	0.002	0.002	
Availability zolles	[0.001]	[0.001]	[0.001]	[0.002]
IT share	2.892***	1.546***	1.482***	1.136*
11 Share	[0.469]	[0.440]	[0.456]	[0.583]
Manufacturing chara		0.499	0.552	0.721**
Manufacturing share		[0.366]	[0.367]	[0.341]
A swi sultavas alsovo	0.077*** 0.053* [0.013] [0.013] 0.002** 0.003* [0.001] [0.00] 2.892*** 1.546* [0.469] [0.44] 0.499 [0.36] -0.91 [0.89] 0.355* [0.113] -0.00 [0.03] -0.19 [0.59] 0.000 [0.19] -0.00 [0.00] -0.01 [0.02] Yes Yes No No 0.581 0.746	-0.914	-1.085	-1.339
Agriculture share		[0.894]	[0.932]	[0.970]
Log (CDD gg)		0.355***	0.260**	0.307*
Log (GDP pc)		[0.113]	[0.120]	[0.175]
Land (Carathal farmantian)		-0.002	0.012	-0.001
Log (Capital formation)		[0.039]	[0.036]	[0.038]
Log (Hybor)		-0.191	-0.939	-1.098
Log (Urban)		[0.595]	[0.688]	[0.705]
Log (TED)		*** 0.053*** 0.031** [3] [0.018] [0.013] [2** 0.003*** 0.002 [1] [0.001] [0.001] [*** 1.546*** 1.482*** [39] [0.440] [0.456] [0.499	0.066	
Log (TFP)		[0.194]	0.031** 0.030** [0.013] [0.014] 0.002 0.002 [0.001] [0.002] 1.482*** 1.136* [0.456] [0.583] 0.552 0.721** [0.367] [0.341] -1.085 -1.339 [0.932] [0.970] 0.260** 0.307* [0.120] [0.175] 0.012 -0.001 [0.036] [0.038] -0.939 -1.098 [0.688] [0.705] 0.075 0.066 [0.167] [0.172] -0.004 -0.002 [0.003] -0.003 -0.008 -0.005 [0.019] [0.018] 0.004] Yes No Yes 0.748 0.774	[0.172]
Log (EDI)		-0.004	-0.004	-0.002
Log (FDI)		[0.003]	[0.003]	[0.003]
Log (Flactuicity, goat)		-0.011	-0.008	-0.005
Log (Electricity cost)		[0.021]	[0.019]	[0.018]
Time a trace of			0.008*	
Time trend			[0.004]	
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes
R-squared	0.581	0.740	0.748	0.774
Observations	225	190	190	190

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Telecom Advisory Services analysis

First, we start in column (i) with a simple estimation without control variables and temporal effects, thus effectively assuming our empirical specification with the restriction $\lambda = \gamma = 0$. All cloud related variables present positive and statistically significant coefficients, as it could have been expected from the literature review. However, this result may be capturing the incidence of other variables linked to digitization and energy productivity, as we may be in the presence of an omitted variable bias. For that reason, in column (ii) we relax the previous assumption

regarding λ and introduce the prepared set of controls in the estimation to check whether the effect of cloud computing on energy productivity is robust to the addition of other factors which may be affecting this latest variable. Results again verify the relevance of cloud-related variables as drivers of energy productivity, although the coefficients for cloud penetration and IT share on the economy now are smaller. The fact that now GDP per capita control presents a positive and significant coefficient suggests that in the estimation without controls, possibly the ICT variables were capturing some effect associated with economic development not absorbed by the country fixed effects. Beyond this adjustment in the magnitude of the effect, it can be said that the incidence of cloud computing on energy productivity seems to be robust to the addition of further control variables.

However, the previous estimates still do not include temporal effects ($\gamma = 0$). The omission of this control may be making ICT-related variables to be capturing some effect attributable to exogenous technological progress. Therefore, in column (iii) we introduce a time-trend in the estimation, which is positive and significant at a 10% level, effectively suggesting a common trend of productivity improvement across the countries considered. As for the coefficients associated with cloud computing, again there is a reduction in its magnitude, thus suggesting that previous estimations were absorbing a higher-than-expected effect. In addition, the coefficient associated with availability zones becomes insignificant from a statistical viewpoint. This is not surprising, as the effect of big cloud hyperscalers has to be analyzed from a transnational perspective, as these investments are usually done to serve groups of countries rather than for domestic demand only. Finally, in column (iv) we test a different alternative to account for temporal factors, introducing year fixed effects. Again, ICT coefficients are slightly reduced, while in the case of the IT share the significance level is now 10%. In this last specification, we are explaining more than 77% of the within-country variation in energy productivity across the period, as denoted by the R-squared. However, none of the year fixed effects are statistically significant, 10 meaning that our preferred estimation should be that reported in column (iii). All in all, we can argue that increases in cloud adoption and a strong IT industry can be considered drivers of energy productivity, and these results are robust to the introduction of fixed effects, an extensive list of control variables, and temporal effects.

In sum, the baseline model regressing cloud adoption, hyperscaler deployment and share of IT value indicates that the deployment of a new availability zone will result in an energy productivity increase of 0.2%, although in some estimates this value becomes insignificant from a statistical viewpoint. As indicated in all the models, when adding multiple controls to model (i) as well as the time trend and year fixed effects, the impact of cloud adoption, and IT share remains significant. In model (ii), availability zone deployment also remains significant when adding controls.

C.2. Cloud Model augmented with spatial effects

We reformulate our baseline model to incorporate these cross-country spatial spillovers derived from the deployment of availability zones. This will consist in

 $^{^{10}}$ The coefficients associated to year dummy variables are not presented in Table 6 for brevity, although are available for the readers upon request.

introducing as explanatory variable a new variable linking a country energy productivity with the deployment of availability zones across neighboring countries:

```
\begin{split} \log(\text{Energy productivity}_{it}) &= \alpha_i + \beta \log(\text{Cloud}_{it}) + \delta \text{ Availability zones}_{it} + \tau \text{ $W$ Availability zones}_{it} \\ &+ \varphi \text{ IT share}_{it} + \lambda \text{ $X_{it}$} + \gamma_t + \varepsilon_{it} \end{split}
```

Where we define the spatial availability zones variable as it follows:

$$W$$
 Availability zones_{it} = $\sum_{j \neq i} w_{ij}$ Availability zones_{jt}

In the previous definition, w_{ij} accounts for a spatial weight that links any country i will all the remaining countries j. This will mean that we expect $\tau > 0$, because of the spatial spillovers. To account for the spatial weights, we developed an (inverse) distance spatial weights matrix, row normalized. This means that all the countries are connected, although with diminishing intensity depending on the geographical proximity. An important remark here is that all world countries were considered in the building of the spatial weight's matrix and in the calculation of the W Availability zones variable. Therefore, even if our sample is restricted to 38 economies, we are considering all countries with availability zones being deployed, and thus, the parameter τ is also capturing the effects of availability zones being deployed in countries not included in our dataset.

After building the spatial variable, we re-estimate the model and present the results in Table C-2. An interesting result is that the availability zones variable is no more significant under any specification, while the opposite happens with the W availability zones variable that accounts for spatial spillovers, which is always positive and significant. This effectively proves that a country being close to a availability zone will derive energy productivity gains. In other words, the deployments of cloud hyperscalers are expected to generate positive effects in neighboring countries that are being served by that infrastructure. The quantification of the effect varies depending on each specific case, but we can provide a specific example to get a measure of the effect: a new availability zone being deployed in Italy will generate an increase of energy productivity of 0.05% in Greece, as assumed as the most conservative impact that of model (i).

In addition, the coefficients associated with the cloud adoption and IT share variables remain positive and significant, reinforcing the relevance of these indicators to explain disparities in energy productivity. Relying in the most conservative of these estimates, we can say that a 1% increase in cloud penetration will yield a 0.023% increase in energy productivity, while on the other hand, if the weight of the IT sector in the economy increases in one percentage point (e.g., from 4% to 5%), energy productivity will increase by 1%.

Table C-2. Spatial model: Fixed Effects spatial estimation of energy productivity drivers

Dep. var.: log (Energy productivity)	(i)	(ii)	(iii)	(iv)
. (d) D	0.037**	0.023**	0.035***	0.029**
Log (Cloud)	[0.015]	[0.011]	[0.011]	[0.014]
A:1-1-:1:	0.001	0.001	0.002	0.002
Availability zones	[0.001]	[0.002]	[0.001]	[0.002]
IAI Assailabilitas non ag	0.044***	0.057**	0.078**	0.077*
W Availability zones	[0.014]	[0.024]	[0.035]	[0.043]
IT share	2.299***	1.466***	1.505***	1.041*
11 Share	[0.458]	[0.375]	[0.351]	[0.529]
Manufacturing share		0.584	0.559	0.616*
Manufacturing Share		[0.367]	[0.365]	[0.338]
Agriculture share		-1.189	-1.106	-1.284
Agriculture share		[0.856]	[0.795]	[0.787]
Log (GDP pc)		0.213	0.263**	0.356**
Log (db) pc)		[0.129]	[0.795] [0.795] [0.13] 0.263** [0.120] [0.120] [0.13] -0.032 [0.33] [0.031] [0.835] -0.258 -0.258 -0.258	[0.175]
Log (Capital formation)		-0.013	-0.032	-0.038
Log (Capital for mation)		[0.033]	[0.031]	[0.034]
Log (Urban)		-0.835	-0.258	-0.486
Log (Orban)		[0.736]	[0.781]	[0.714]
Log (TFP)		0.184	0.176	0.126
Log (TTT)		[0.127]	[0.124]	[0.133]
Log (FDI)		-0.002	-0.001	0.000
Log (1 D1)		[0.003]	[0.003]	[0.003]
Log (Electricity cost)		-0.002	-0.001	0.001
nog (nicetricity cost)		[0.014]	[0.014]	[0.013]
Time trend			-0.009	
Time trend			[0.005]	
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	Yes
R-squared	0.620	0.778	0.783	0.798
Observations	225	190	190	190

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Telecom Advisory Services analysis

As indicated in all the models, even when adding multiple controls to model (i) as well as the time trend and year fixed effects, the impact of cloud adoption, spatial effects, and IT share remains significant.

C.3. Model accounting for dynamic effects

While following a different empirical strategy, Atalla and Bean (2017) argue that there is a dynamic relationship between current and past values of energy productivity. To address this possibility in our model, we replicate previous

estimates but now including a lag of the dependent variable as right-hand regressors.¹¹ Therefore, the empirical specification turns into the following:

```
\begin{split} \log(\text{Energy productivity}_{it}) &= \alpha_i + \theta \ \log(\text{Energy productivity}_{it-1}) + \beta \log(\text{Cloud}_{it}) \\ &+ \delta \ \text{Availability zones}_{it} + \tau \ W \text{Availability zones}_{it} + \varphi \ \text{IT share}_{it} + \lambda \ X_{it} \\ &+ \gamma_t + \varepsilon_{it} \end{split}
```

Based on the previous equation, it is anticipated that energy productivity will be influenced by its own previous value. From an econometric viewpoint, incorporating the lagged dependent variable as a regressor is likely to result in a correlation with the fixed effects in the error term. This correlation creates a "dynamic panel bias" as described by Nickell (1981) and violates the necessary assumptions for consistency in Ordinary Least Squares (OLS) estimators with fixed effects.

Since our equation cannot be estimated using the traditional fixed effects approach due to these circumstances, we need to employ an estimation strategy that considers country-specific effects without encountering the "dynamic panel bias". In contrast to the traditional fixed effects approach, the estimator proposed by Arellano and Bond (1991) using the Generalized Method of Moments (GMM) is specifically designed for dynamic panels, without incurring in the biases associated with the OLS estimator for these models. The estimations with robust standard errors are presented in Table C-3.

¹¹ We tested a model including also a second lag of the dependent variable as regressor, although we discarded it as it was never significant. These results are available upon request.

Table C-3. Arellano-Bond dynamic panel of electricity productivity drivers

Dep. var.: log (Energy productivity)	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Log (Floatricity productivity)	0.271**	0.203**	0.214**	0.233**	0.200**	0.219**
Log (Electricity productivity) t-1	[0.106]	[0.089]	[0.094]	[0.097]	[0.092] 0.035** [0.017] 0.002 [0.001] 0.073*** [0.022] 0.732 [0.558] 0.532** [0.233] 0.814 [1.096] 0.399***	[0.104]
Log (Cloud)	0.059***	0.037***	0.034**	0.037**	0.035**	0.037**
Log (Cloud)	[0.012]	[0.014]	[0.017]	* 0.233** 0.200** [0.097]	[0.018]	
Availability zones	0.002**	0.002*	0.002**		233** 0.200** .097] [0.092] .037** 0.035** .017] [0.017] .001 0.002 .001] [0.001] 0.073*** [0.022] .421 0.732 .736] [0.558] 47*** 0.532** .163] [0.233] .658 0.814 .142] [1.096] .36*** 0.399*** .167] [0.097] .014 -0.026 .040] [0.038] .070* -0.587 .557] [0.800] .032 0.086 .141] [0.138] .001 -0.000 .003] [0.003] .014 0.007 .010] [0.009]	0.001
Tivaliability Zolies	[0.001]	[0.001]	[0.001]	[0.001]		[0.001]
W Availability zones						0.049* [0.027]
	1.239***	0.846	0.724	0.421		0.362
IT share	[0.358]	[0.711]	[0.710]			[0.635]
	[0.000]	0.462**	0.456*			0.621***
Manufacturing share		[0.227]	[0.236]			[0.171]
		0.733	0.900		0.200** [0.092] 0.035** [0.017] 0.002 [0.001] 0.073*** [0.022] 0.732 [0.558] * 0.532** [0.233] 0.814 [1.096] * 0.399*** [0.097] -0.026 [0.038] -0.587 [0.800] 0.086 [0.138] -0.000 [0.003] 0.007 [0.009]	0.625
Agriculture share		[1.066]	[1.077]			[1.133]
		0.454***	0.453***			0.441***
Log (GDP pc)		[0.112]	[0.100]	[0.167]	36*** 0.399*** 167] [0.097]	[0.165]
		0.000	0.004	-0.014	-0.026	-0.030
Log (Capital formation)		[0.044]	[0.045]	[0.040]	[0.038]	[0.037]
. (11.1.)		-0.861*	-0.887	-1.070*	97] [0.092] 97** 0.035** 0 17] [0.017] 01	-0.875
Log (Urban)		[0.494]	[0.663]	[0.557]	[0.800]	[0.594]
L (TED)		0.011	0.007	0.032	0.086	0.058
Log (TFP)		[0.141]	[0.139]	[0.141]	[0.138]	[0.139]
Log (EDI)		-0.002	-0.002	-0.001	[0.092] 0.035** [0.017] 0.002 [0.001] 0.073*** [0.022] 0.732 [0.558] 0.532** [0.233] 0.814 [1.096] 0.399*** [0.097] -0.026 [0.038] -0.587 [0.800] 0.086 [0.138] -0.000 [0.003] 0.007 [0.009] -0.012** [0.005] No	-0.000
Log (FDI)		[0.004]	[0.003]	[0.003]	[0.003]	[0.003]
Log (Floatricity cost)		0.009	0.009	0.014	0.007	0.013
Log (Electricity cost)		[0.011]	[0.011]	[0.010]	[0.009]	[0.009]
Time trand			0.000		-0.012**	
Time trend			[0.004]		[0.005]	
Year fixed effects	No	No	No	Yes	No	Yes
Observations	183	135	135	135	135	135

Note: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Source: Telecom Advisory Services analysis

In all cases, the dynamic effects seem to account, as energy productivity seems to depend on its past values. More importantly for our purposes, the economic effect of cloud computing penetration seems to be unchanged after following this estimation strategy. Moreover, the coefficient associated with availability zones seems to be more relevant than in previous estimates, being significant even when incorporating the trend effects (column (iii)), although it loses significance in further estimates. In any case, the spatial effects remain relevant, as denoted by the coefficient associated to the spatial lag of availability zones.

Changes arise with respect to the IT share variable, as now it loses significance when introducing the set of control variables. This means that controlling for structural factors denoted in previous values of energy productivity reduces the relevance of the IT sector as a regressor, possibly because now the negative side of IT (such as rebound effects and high energy consumption from electronic devices) seem to counteract the positive effects.

As for the control variables, income per capita remains an important driver of energy productivity, while now, after controlling for past values of the dependent variable, the manufacturing weight exhibits a positive and significant sign. In addition, the urban variable presents a negative and significant (at 10%) coefficient in some of the estimates, suggesting that the migration of people to urban areas can be associated with them starting to conduct more energy intensive activities.

APPENDIX D. DATA SOURCES FOR COMPARATIVE ANALYSIS OF ENERGY PRODUCTIVITY BY SECTOR

Value added for each economic sector was extracted from the Eurostat database.¹² As for electricity consumption, Eurostat also reports data for all manufacturing industries but does not provide data on electricity consumption for agriculture, forestry and fishing, and IT. In this case, agriculture and fishing electricity consumption data was obtained from International Energy Agency (IEA).¹³ While those estimates do not contemplate forestry, we believe that electricity consumption of this subsector can be considered *de minimis*.

Table D-1. Data sources for calculating sector energy productivity

Sector	Detailed definition	Data source for Value Added	Data source for electricity consumption
Food	Manufacture of food products; beverages and tobacco products	Eurostat	Eurostat
Textile	Manufacture of textiles, wearing apparel, leather and related products	Eurostat	Eurostat
Wood	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Eurostat	Eurostat
Paper	Manufacture of paper and paper products	Eurostat	Eurostat
Rubber and plastic	Manufacture of rubber and plastic products	Eurostat	Eurostat
Metals	Manufacture of basic metals	Eurostat	Eurostat
Agriculture	Agriculture, forestry and fishing	Eurostat	IEA
IT	Information and Communication	Eurostat	Estimated from data provided by IEA, ITU, and Data Center Map

Source: Telecom Advisory Services analysis

Electricity consumption for the IT sector had to be estimated from several data sources by relying on the following approach (see figure D-1).

¹²

 $https://ec.europa.eu/eurostat/databrowser/view/nrg_d_indq_n_custom_9203481/default/table?lang=en$

¹³ https://www.iea.org/data-and-statistics/data-tools/energy-statistics-data-browser?country=WORLD&fuel=Energy%20consumption&indicator=ElecConsBySector

Electricity consumption for data centers Source: IEA Global electricity Electricity Gross value Calibration of consumption for added per TJ for consumption for derived data IT by country IT sector Electricity consumption for telecom networks Number of data Electricity Gross value consumption for added for IT by centers and Source: IEA IT for France, internet traffic country Germany, and per country Source: EUROSTAT Netherlands Sources: ITU; Data Center Мар Source: Montevecchi. Reporrt to the EC Original data sources Calculated fields

Figure D-1. Methodology for estimating energy productivity in the IT sector

Source: Telecom Advisory Services

As indicated by the IEA, the two primary sources of electricity consumption associated with the IT industry are telecommunication networks, and data centers. The IEA reports values for both segments for 2015 and projects 2022 levels based on an interval.¹⁴ Based on a constant compound annual growth rate and on the conservative forecast provided by IEA for 2022, we estimate a 2021 global consumption of electricity of 254 million MWh generated by telecommunications network traffic and 234 million MWh by data centers. By considering the global data traffic for 2021 (3,310 exabytes, estimated from IEA), and the total number of data centers (5,065 as detailed in Data Center Map¹⁵), we estimate that, on average, each exabyte of data traffic requires annually 76,694.51 MWh, while each data center consumed on average 46166.70 MWh.

As a reliability check, we compare the estimated values of IT electricity consumption with the figures estimated in Montevecchi et al. (2020). The authors estimated electricity consumption based on microeconomic drivers for cloud computing for France, Germany, Netherlands and the United Kingdom up to 2018: 11.68, 15.50, 5.40 and 12 million MWh, respectively (see figure 18, page 58). These figures were calculated through chain ratios for the diverse IT components needed to deliver cloud (server, storage, network) and the infrastructure (cooling, UPS, other).

Our data is based on 2021, so it is expected to represent higher values than that reported in Montevecchi et al (2020). Before conducting the direct comparison, we first must identify which share of our estimated total IT electricity consumption is attributable to cloud. To do so, we rely on Cisco figures for 2019, where nearly 90% of the workloads and compute instances in data centers in Western Europe were estimated to be cloud workloads and only 10% traditional workloads (Montevecchi

 $^{^{14}\,}https://www.iea.org/energy-system/buildings/data-centres-and-data-transmission-networks#tracking$

¹⁵ https://www.datacentermap.com/datacenters/

et al, 2020). On the other hand, measured by data center IP traffic, cloud computing will be responsible for 93% of the traffic in Western Europe in 2019 (Cisco, 2018).

Therefore, by applying to our estimate of data center electricity consumption a share of 90% attributable to cloud, and to our estimates of data traffic consumption a share of 93% (also attributed to cloud), we can estimate the cloud computing electricity consumption in 2021 for France, Germany, Netherlands and the United Kingdom seems to be very consistent with Montevecchi et al. (2020) estimations for 2018 (Table D-2).

Table D-2. Calculation of electricity consumption for IT sector (2021)

	F	Estimations			
Country	Electricity	Electricity	Electricity	Electricity	of
	consumption of	consumption of	consumption	consumption of	Montevecchi
	internet traffic	Data Centers	of IT sector	Cloud computing	et al. (2020)
	(MWh) for year	(MWh) for year	(MWh) for	(MWh) for year	(MWh) for
	2021	2021	year 2021	2021	year 2018
France	6758202.629	7709692.279	14467892.13	11681912.12	11680000
Germany	8088100.915	11402956.34	19491057.26	15504004.07	15500000
Netherlands	1570090.145	5632229.506	7202319.651	5402745.989	5400000
United	10483955.61	13203424.45	23687380.06	21633161.75	12000000
Kingdom					

Sources: International Energy Agency; International Telecommunication Union; Data Center Map, Telecom Advisory Services analysis

Having validated our estimated electricity consumption for the IT sector in each country, and the value added for this sector reported in Eurostat, we can now calculate the electricity efficiency of this industry and compare it with the rest of the sectors across each country.