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From Physical to Digital Things: What does IoT mean for economic growth?

Aquije Ballon, Harry; Bahia, Kalvin; Castells, Pau

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Abstract

While mobile technologies have already connected billions of people, the Internet of Things (IoT) is now adding all kinds of devices to the digital ecosystem. The potential benefits of connecting the physical world to the internet are vast, but not well understood. This study provides a contribution to quantify the contribution of IoT to economic growth. By leveraging a unique dataset that measures IoT connections by vertical industry across 163 countries between 2010 and 2022, we find that IoT made a significant contribution to GDP growth. On average, a 10 percentage point increase in IoT connections per inhabitant increased GDP by 0.7% in LMICs and 0.5% in HICs. We find that this impact is primarily driven by enterprise IoT, accounting for 80% of the total effect, while consumer IoT contributed 20%.

JEL Classifications: O47 - Empirical Studies of Economic Growth • Aggregate Productivity • Cross-Country Output Convergence, 033 -Technological Change: Choices and Consequences • Diffusion Processes, L96 - Telecommunications, O11 - Macroeconomic Analyses of Economic Development, O4 - Economic Growth and Aggregate Productivity

1. Introduction

We are entering an era of more advanced technologies in AI and IoT, and with increasing adoption and use cases there is a need to better understand the potential economic impacts these could enable. IoT describes the coordination of multiple machines, devices and appliances connected to the internet through multiple networks. According to GSMA Intelligence, at the end of 2023 there were 2[1](#page-2-0) billion IoT connections. These are expected to almost double by 2030.¹ By connecting the physical world to the internet, IoT can impact economic growth through similar channels that ICT benefits households and industries. That is in the form of spillovers leading to greater productivity, a more efficient allocation of resources, and new opportunities for innovation.

Despite its growing importance and range of applications, the literature on the economic impacts of IoT is still limited. Some studies look at macro-economic outcomes, for example the effects on productivity and employment (see for example Espinoza et al. (2020); Edquist et. al. (2021); Clemente (2022)). Other empirical studies have studied the effects on the global value chain in specific industries, but the data is limited and restricted to specific IoT technologies (Egwuonwu et. al. (2022); Wang et. al. (2021)). Our study aims to fill this gap and establish whether a causal link between IoT adoption and economic growth exists.

This paper leverages a unique database on IoT connections covering 163 countries in the 2010- 2022 period. This database includes two broad categories of IoT: consumer IoT and enterprise IoT. Combining these with data on digital technologies and economic indicators we find empirical evidence of the contribution of IoT to productivity and economic growth in the period of study. Specifically, a 10% increase in total IoT connections per inhabitant increased GDP by 0.7% in LMICs and 0.5% in HICs. We also find that enterprise IoT accounted for 80% of the total effect, while consumer IoT contributed 20%.

The remainder of this paper is organised as follows. Section 2 presents our research question and how it fits with the existing empirical literature. Section 3 describes the data and Section 4 details the empirical strategy. Section 5 provides results and Section 6 summarises key findings and policy recommendations, as well as offering suggestions for further research.

¹ GSMA Intelligence, 2023, IoT connections forecast to 2030.

2. Literature review

In the last decade the pace of development of digital technologies has dramatically increased creating a stronger connection between the physical and digital world. These new technologies include artificial intelligence, IoT, cloud computing and edge computing, among others. Despite the increasing importance and use of IoT there is still limited academic literature on the economic impacts of this technology.

In the macroeconomic literature of IoT, the focus has been on productivity, GDP and employment. In an empirical study, Edquist et al. (2021) find that a 10 percent increase in the growth of IoT connections per inhabitant is associated with a 0.23 percent increase in total factor productivity (TFP) growth. The authors estimate a standard spillovers equation in a panel of 82 countries with data from 2010 to 2018. Using growth accounting parameters they calculate a contribution to GDP of \$849 billion per annum in the 2018-2030 period.

Espinoza et al. (2020) use the growth accounting framework to evaluate the likely impact of the IoT on productivity in Europe. The results show a positive but small impact, given the low rates of adoption. On a similar research García (2015) proposes a framework based on the multifactor productivity (MFO) approach for analysing the impact of IoT on economic growth.

Clemente (2022) investigates the relationship between IoT and labour market outcomes. Relying on static and dynamic panel data estimators in a sample of 107 countries from 2010 to 2019, the author finds a positive and significant relationship between IoT connections per 100 inhabitants and employment in OECD countries. The effect is mostly driven by the positive relation with the services sector.

Frontier Economics (2018) estimates a Cobb-Douglas production function with M2M connections as variable of interest and GDP and gross value added as dependent variables. The study covers a sample of 27 EU and OECD countries between 2012 and 2015. The authors find that in the industry and services sector a 10% rise in M2M connections leads to an increase of 0.7% in GDP, although it does not address potential endogeneity concerns. In another study, Manyika et al. (2015) estimate a potential economic impact of IoT of \$11.1 trillion per year in 2025 for IoT applications in nine settings. They also find that business-to-business (B2B) applications are more important than consumer application and can generate nearly 70 percent of potential value enabled by IoT.

GSMA (2019) finds that the productivity benefits to businesses from the use of IoT accounted for \$175 billion or 0.2% of GDP in 2018. Over half of these benefits come from the manufacturing sector. These estimates are calculated using the GSMA Intelligence IoT Enterprise Survey 2018, in combination with assumptions on IoT business adoption rate, and sector value add from the OECD Input-Output table. A more detailed review of the relevant macroeconomic studies is included in Appendix 1.

In the microeconomic literature of IoT the focus has been at the corporate level. In a recent study Wang et al. (2021) use a difference-in-differences estimator to study the economic consequences of IoT adoption in China on earnings management activities. They find that IoT adoption reduces firms earnings management, meaning that by reducing human involvement in production and operation processes, IoT can strengthen key asset monitoring. In this way it can improve the financing and investment efficiency of the real economy, mitigate the risk of stock price crashes, and improve capital market resource allocation efficiency.

Egwuonwu et al. (2022) using data of an online survey of UK agri-food retailers find that blockchain technology when combined with IoT will strengthen the global value chain. The mechanisms will be through improving in scalability, security, and traceability combined with the IoT ecosystem.

Our study uses a unique database with total IoT connections by verticals, which is different from licensed cellular IoT connections, the metric commonly used in the literature (Edquist et al. (2021), Clemente ([2](#page-4-0)022)).² It should be noted that licensed cellular IoT connections represents a small proportion of total IoT. In 2022, it accounted for 15% of total IoT connections, while the majority corresponded to other access technologies, including unlicensed LPWA (e.g. SigFox, LoRa), short range (e.g. Wi-Fi, Zigbee), fixed, Ethernet, satellite and others. Therefore, our study is the first to capture the effect of total IoT devices and technologies in the economy. This also gives us the possibility to test for heterogeneous effects between consumer IoT and enterprise IoT. Moreover, exploiting our extensive sample of countries we could differentiate the impacts for LMICs and HICs, providing valuable policy insights. Finally, we also focus on ways to address the potential endogeneity, one of them being the use of dynamic panel data models.

² Licensed cellular IoT is the sum of cellular M2M and licenced LPWA. Licenced LPWA refers to NB-IoT and LTE-M.

3. Data

Our analysis is based on country-level data for 163 countries in the 2010-2022, period. The sample of countries is divided into low-and-middle income countries (LMICs) representing 70% of the total, and high-income countries (HICs) accounting for 30%. These are defined based on the World Bank's income classifications.^{[3](#page-5-0)} The list of countries included in the study, split by LMICs and HICs is presented in Appendix 3.

For data on IoT, we leverage a database sourced from GSMA Intelligence with IoT connections by verticals.

IoT connections

GSMA Intelligence defines the Internet of Things (IoT) as devices capable of two-way data transmission (excluding passive sensors and RFID tags). It includes connections using multiple communication methods such as cellular and short range. It excludes PCs, laptops, tablets, ereaders, data terminals and smartphones. In simple terms, IoT is about connecting everything to the internet, and it can have applications for households and businesses across all economic sectors.

In the 2010-2022 period, the number of IoT connections has rapidly increased passing from 0.4 to 2.4 IoT connections per capita. The countries with the highest IoT adoption were located in North America and Western Europe, followed by Asia Pacific. On the opposite side, Africa had the lowest IoT connections per capita. Figure 1 presents a map with the IoT connections per capita by country in 2022.

³ See [World Bank Country and Lending Groups.](https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups) Our analysis is based on historical classifications. Available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

Figure 1: IoT connections per capita in 2022

Source: GSMA Intelligence

GSMA Intelligence maintains two databases for IoT connections, the first corresponding to licensed cellular IoT connections, and the second to total IoT connections by verticals. The latter is segmented into two broad categories: consumer IoT and enterprise IoT. Figure 2 presents the average IoT connections per capita in the period of study, split by consumer IoT and enterprise IoT. The detail of the IoT vertical splits is presented in Appendix 2. In the early years of the roll-out of IoT technologies, the majority of connections were on the consumer segment representing around 70% of the total. However, in the last five years, the pace of growth of enterprise IoT has accelerated overtaking the growth of consumer IoT. In 2022, consumer IoT represented 55% of the global IoT connections and enterprise IoT accounted for the remaining 45%. Based on GSMA Intelligence forecasts, by 2030, 63% of total connections will be enterprise IoT connections, reflecting more enterprises adopting IoT to drive digital transformation, and existing IoT deployments scaling up. Such business transformation is underpinned by data, giving rise to software tools (AR, Al/ML) and cloud.^{[4](#page-6-0)}

⁴ GSMA Intelligence (2021), IoT market update: assessing disruption and opportunities, forecasting connections to 2030.

Figure 2: IoT connections per capita, by verticals in the 2010-2022, period

Source: GSMA Intelligence

Other data

The macroeconomic variables used in our study are gathered from the International Monetary Fund (IMF) World Economic Outlook (April 2024), specifically total GDP, and capital investment, which are both expressed in constant 2017 PPP USD. Data on labour force participation is sourced from the World Bank's World Development Indicators (WDI 2024) and International Labour Organization, while data on mean years of schooling (used as a proxy for human capital) is sourced from the UN Human Development Index. We also use data on mobile connections from GSMA Intelligence, which is primarily sourced from operators' public reports, and data on fixed broadband penetration from the ITU. The data on the sectoral shares of GDP is gathered from the UN National Accounts Official Country Data. A full list of indicators used, along with the relevant sources and a set of descriptive statistics, is provided in Appendix 3.

4. Empirical Strategy

Production function

We use the aggregate production function approach where GDP is a function of fixed capital, labour, human capital and digital infrastructure and services – the latter includes the adoption of communication technologies more generally, including mobile and fixed broadband, as well as IoT technologies. This framework is consistent with the approach employed in the existing literature that has assessed the macroeconomic impacts of mobile and fixed broadband technologies.^{[5](#page-8-0)}

In our empirical specification, the output of a country i at time t (GDP_{it}) depends on its physical capital (total investment) (K_{it}) , labour force participation (L_{it}) and mean years of schooling (schooling_{it}) as a proxy for human capital. The main variable of interest is IoT adoption (IOT_{it}), but we also include fixed broadband adoption ($Fixed_BB_{it}$) and mobile adoption ($Mobile_{it}$). The terms μ_i and θ_t are parameters for country and time (year) fixed effects. The former captures any time-invariant heterogeneity at the country-level (such as geographic characteristics), while the latter controls for time-bounded macroeconomic shocks that impact every country at the same time (such as the Covid-19 pandemic). This addresses concerns that underlying country characteristics lead to different levels of economic growth by conditioning on a set of covariates. Equation 1 becomes our OLS-FE estimator.

$$
log(GDP_{it}) = \beta_0 + \beta_1 log(K_{it}) + \beta_2 log(L_{it}) + \beta_3 log(schooling)_{it} + \beta_4 log(FixedBB_{it}) + \beta_5 log(Mobile_{it}) + \beta_6 log(log(IoT_{it}) + \mu_i + \theta_t + \varepsilon_{it}
$$
 (1)

The effect of IoT on economic growth for LMICs and HICs is modelled in equation 2, by interacting IoT adoption with the binary variable HICs, which takes the value of 1 for HICs and 0 otherwise.

$$
log(GDP_{it}) = \beta_0 + \beta_1 log(K_{it}) + \beta_2 log(L_{it}) + \beta_3 log(schooling)_{it} + \beta_4 log(FixedBB_{it}) +
$$

$$
\beta_5 log(Mobile_{it}) + \beta_6 log(IoT_{it}) + \beta_7 (HICs_{it}) + \beta_8 log(IoT_{it}) * HICs_{it} + \mu_i + \theta_t + \varepsilon_{it}
$$
 (2)

While equations 1 and 2 are used to assess the relationship between IoT adoption and GDP growth, we are also interested in understanding whether consumer IoT or enterprise IoT can have different effects on the economy. To do this, we estimate equation 3, which modifies the above strategy by including the breakdown by type of IoT.

$$
log(GDP_{it}) = \beta_0 + \beta_1 log(K_{it}) + \beta_2 log(L_{it}) + \beta_3 log(schooling)_{it} + \beta_4 log(FixedBB_{it}) +
$$

$$
\beta_5 log(Mobile_{it}) + \beta_6 log(10T_{consumer_{it}}) + \beta_7 log(10T_{enterprise_{it}}) + \mu_i + \theta_t + \varepsilon_{it}
$$
 (3)

⁵ See for example Czernich et al (2011), Gruber et al (2014), Koutroumpis (2019), ITU (2020) and Briglauer et al (2022).

The benefits of IoT can be spread across all industries. However, some industries are more intensive in the use of IoT. For example, there are many applications of IoT in the manufacturing sector (GSMA (2018)). In order to control for the effects that the industry composition can have on the IoT economic impacts, we include as controls the shares of GDP in different industries. For this purpose we define eight sectors, in line with the UN's value added by industries data.^{[6](#page-9-0)} The economic sectors are presented in Appendix 4.

Limitations

Our empirical strategy is based on the exogeneity assumption, meaning that IoT can be seen as randomly allocated within countries. However, this is not always the case and it can be that countries that deployed this technology first or with more intensity are those that have better conditions to promote economic growth (positive bias) or the other way around (negative bias). We control for observable factors that explain economic growth in our empirical specifications. However, some of these factors are unobservable and cannot be modelled, or even if some of them are prone to measure there is not available data.

There is therefore a potential endogeneity in the form of omitted variables bias or simultaneity. One way of addressing potential endogeneity in these cases is the use of dynamic panel data models. We use dynamic panel data models, such as the Arellano-Bond (Arellano and Bond, 1991) and the Blundell-Bond (Blundel and Bond, 1998) Generalized Method of Moments (GMM) estimators. Dynamic panel data models include past values of the dependent variable to capture its short-run autoregressive behaviour. In our model specification, we assume that the level of GDP in a country is persistent and depends on its past values (see equations 4 and 5).

While dynamic panel data models are appealing to deal with endogeneity, they also have some limitations. First, these models are very sensitive to the number of lags and type of transformation to apply to the model (difference GMM or system GMM). Including too many lags can overfit the model introducing more bias, and also weakening the diagnostic tests. Second, a dynamic model captures better the evolution of the economy over time, however, it may not control for the simultaneity bias arising from the market interactions in the same period. Following the same identification strategy described before we estimate dynamic panel data models for the sample of all countries (equation 4).

 $log(GDP_{it}) = \beta_1 log(GDP_{it-1}) + \beta_2 log(K_{it}) + \beta_2 log(L_{it}) + \beta_3 log(schooling)_{it} + \beta_4 log(FixedBB_{it}) +$ $\beta_5 \log (Mobile_{it}) + \beta_6 \log (IoT_{it}) + \mu_i + \theta_t + \varepsilon_{it}$ (4)

Equation 5 captures the heterogenous effects for income level, by introducing the interaction between IoT adoption and the binary variable HICs.

⁶ The data was downloaded on May 2024 from: https://data.un.org/Data.aspx?d=SNA&f=group_code%3A204

 $log(GDP_{it}) = \beta_1 log(GDP_{it-1}) + \beta_2 log(K_{it}) + \beta_3 log(L_{it}) + \beta_4 log(schooling)_{it} + \beta_5 log(FixedBB_{it}) +$ $\beta_6 \log(Mobile_{it}) + \beta_7 \log(IoT_{it}) + \beta_8 (HICs_{it}) + \beta_9 \log(IoT_{it}) * HICs_{it} + \mu_i + \theta_t + \varepsilon_{it}$ (5)

Equation 6 captures the effects of IoT by verticals defined as consumer IoT and enterprise IoT.

 $log(GDP_{it}) = \beta_1 log(GDP_{it-1}) + \beta_2 log(K_{it}) + \beta_3 log(L_{it}) + \beta_4 log(schooling)_{it} + \beta_5 log(FixedBB_{it}) +$ β_6 log (Mobile_{it}) + $\beta_7(IoT_consumer_{it}) + \beta_8(IoT_enterprise_{it}) + \mu_i + \theta_t + \varepsilon_{it}$ (6)

We are also considering alternative strategies to address the potential endogeneity, including the use of instrumental variables coming from policy or regulatory frameworks, or alternative technologies that could have driven the adoption of IoT in a country like Sigfox technology. Another option that is being explored is the use of the Shift-Share Instrumental Variables, being the shift the growth in the global IoT connections by vertical, and the shares the initial distribution of the shares of GDP by industry before the IoT deployment. Note that the shifts vary at a global level, while the industry and shares move at the country level. We will report on these strategies in the next version of the paper.

5. Results

This section presents static panel data and dynamic panel data results for the effect of IoT on the economy, measured by the log of total GDP. The results are split by consumer IoT and enterprise IoT. We also present the impacts for LMICs and HICs.

Two-way FE results

First, we present the main results using the two-way fixed-effects (FE) panel data estimator. Table 1 shows the impacts on GDP growth for the countries that have had IoT connections in the 2010– 2022 period. The results suggest that an increase in IoT connectivity has a positive and statistically significant impact on GDP. Across LMICs, a 1% increase in total IoT connections per capita increased GDP by 0.073%. Across HICs, a 1% increase in total IoT connections per capita increased GDP by 0.047%. In the period of study the contribution of IoT to the economy was 1.5 times higher in LMICs compared to HICs. It can be explained because in the last years the growth in advanced economies has slowed down while developing economies have had stronger performance, in these countries the general well-being is lower and there is more room for improvement and efficiency gains when adopting new technologies. Moreover, holding all other variables constant HICs have had 0.091% higher GDP compared to LMICs.

Table 1: Two-way FE results for effect of log IoT on log GDP between 2010 and 2022 Source: GSMA Intelligence

***p<0.01, **p<0.05, *p<0.1. Robust standard errors are presented in parentheses.

The results by verticals confirm the importance of enterprise IoT for boosting economic growth (Table 1 column (3)). Consumer IoT was the most prominent use case in the early years of IoT. However, enterprise IoT has gained traction in the last years. Across all countries, a 1% increase in consumer IoT connections per capita increased GDP by 0.014%. Moreover, a 1% increase in enterprise IoT connections per capita increased GDP by 0.063%, meaning that the contribution of enterprise IoT was 4.5 times higher than consumer IoT, in the 2010-2022 period.

The results for the inclusion of the sectoral shares of GDP as controls are presented in Table 1 column (4). After controlling for the sectoral composition in the economy, and the effect that it has on GDP we still find a positive and significant effect of IoT on economic growth, showing that across all countries a 1% increase in total IoT connections per capita increased GDP by 0.054%. Note that when including the shares of GDP as a control variable the sample of countries reduces from 163 to 125, which is explained because this variable is not available for all the countries in our original sample.

Dynamic panel data results

We estimated dynamic panel data models using the Arellano-Bond GMM estimator (Arellano and Bond, 1991). In these specifications GDP depends on the same set of controls as previously, but also on the lag value of GDP in the year before. We also include seven lags as instruments in the model in columns (1) and (2), and eight lags as instruments in columns (3) and (4). Table 2 presents the results, column (1) for total IoT connections, column (2) for the sample of LMICs and HICs, column (3) for the split by verticals, and column 4 for total IoT connections including as control the shares of GDP. We find positive and significant results of the effects of IoT in the economy in line with results of the two-way FE models.

The diagnostics test are as expected, rejecting the hypothesis of first order autocorrelation, and no rejecting the hypothesis of second order autocorrelation. We also present the Hansen test even though in some of our models we do not reject the null hypothesis of exogenous instruments.

We can see that the lag of the GDP has a large explanatory power in the model, and also the effect of total IoT connections, and consumer IoT is positive after the inclusion of the instrumental variables, though significant at the 5% level. The coefficients are of similar magnitude at the ones obtained in the main specification. In column (2) we can see that the effect of IoT connections is significant for LMICs but not for HICs using the dynamic panel data estimator. In column (3) the impact of enterprise IoT is positive and significant, but consumer IoT is not statistically significant. Moreover, in column (4) when including as additional controls the shares of GDP the sample of countries reduces to 125 and the effect of IoT is positive and significant. The results of the dynamic panel data models show that a 1% increase in total IoT connections per capita increased GDP between 0.038% and 0.048%.

***p<0.01, **p<0.05, *p<0.1. Robust standard errors are presented in parentheses.

6. Conclusions

This study represents an important contribution to empirical literature of the impacts of ICTs in the economy, particularly digital technologies that have significantly increased in the last decade. By leveraging a novel database on IoT connections by verticals across 163 countries in the 2010-2022 period, we find that IoT adoption has a significant impact on GDP growth. On average, a 10 percentage point increase in total IoT connections per inhabitant increased GDP by 0.7% in LMICs and 0.5% in HICs. The larger economic contribution comes from enterprise IoT accounting for 80% of the total effect, while consumer IoT represented 20%.

These results have important implications for policymakers. Enterprise IoT has gained momentum in recent years and by 2030, more than 60% of total connections will be enterprise IoT connections. Governments can implement policies to stimulate IoT adoption by businesses, which will enhance competitiveness and benefit the wider economy. Moreover, some industries were found to drive larger economic benefits, for example manufacturing, financial and insurance activities and the services sector. Our results confirm the importance of enterprise IoT and present evidence that can help policymakers in LMICs and HICs to design better policies according with the requirements of each country. Consumer IoT has also made an important contribution to GDP, and will continue to grow.

Our study contributes to the empirical literature of the macroeconomic effects of IoT. We exploit a unique database of IoT connections by verticals, that allow us to differentiate the contribution for consumer IoT and enterprise IoT. We were also able to calculate the impacts for LMICs and HICs, giving valuable insights for policy makers. Additionally, we control for the potential endogeneity by using dynamic panel data models, however, we are aware of the limitations of this approach, and we are working on further identification strategies that will be presented in the next version of the paper.

One of the key components that will support the development of IoT use cases across industries is a better and more reliable connectivity. In this context, 5G is the technology that can provide benefits to the IoT that are not available with 4G or other technologies. As indicated by GSMA (2019) these can be grouped under three main categories: enhanced mobile broadband (eMBB), massive IoT (known as mMTC), and critical communications.

We assume that IoT contributes to the economy in the form of productivity spillovers, similar to the more traditional ICTs, but the effects of IoT can be different especially considering the rapid advancement of new technologies, and the interaction of IoT with AI, cloud computing, and edge computing, giving the possibility to introduce changes in the economy not seen before. Even though there is some microeconomic literature on the benefits of IoT, the evidence is limited. Therefore, we recommend further studies to investigate the intermediate outcomes that channel these effects. Likewise, different outcomes should be measured (employment, inequality, formalisation, etcetera) to have a better understanding on how the IoT is driving improvements in general well-being.

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Appendix 1: Literature review of IoT macroeconomic impact studies

Table A1 summarises the main studies that have attempted to quantify the macroeconomic impacts of IoT more generally.

Appendix 2: IoT vertical splits

Table A2 sets out the industry splits for consumer IoT and enterprise IoT. The distinction is primarily based on IoT device ownership, but it should be noted that "consumer" is a loose term as some devices (e.g. smart TVs) could be used in non-residential environments.

Table A2: IoT by verticals

Appendix 3: Data description and **statistics**

Table A3.1 sets out the final list of countries included in the study, for the sample of LMICs and HICs. The income classification presented in the table below is based on the latest WB income classification 2022. However, in the study the income classification was applied for each year based on the WB historical income classification.

Table A3.1: List of countries included in the study

Sample LMICs

Sample HICs

Data description

Table A3.2 lists the variables we consider as well as their definitions and sources.

Table A3.2: Country-level control variables

Descriptive statistics

Tables A3.3 and A3.4 present the descriptive statistics for the sample of LMICs and HICs that have deployed IoT connections in the 2010-2022, period.

Table A3.3: Descriptive statistics – sample LMICs

Table A3.4: Descriptive statistics – sample HICs

Appendix 4: Industries

Table A4 presents the link between the United Nations value added by industries, and the sectors considered in the study.

Table A4: Correspondence between United Nations Industries and economic sectors

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