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Connected and Employed:

Empirical Evidence On The Internet of Things in a Panel of Countries

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Abstract: The Internet of Things (IoT) is a network of interconnected devices and objects, able to communicate with each other, the physical world and the Internet. It has a wide range of applications, from automation to data collection, in a number of industries and sectors. However, the literature on its economic impacts is limited. This thesis aims at filling some of the gap by investigating whether a significant relationship between IoT usage and labor demand exists. To do this, I construct a panel of country-level data on the number of Internet of Things connections in 107 countries over the early years of IoT introduction (2010-2019). Applying two-way fixed effects and dynamic panel models, I find evidence of a positive and significant relationship between IoT connections per 100 inhabitants and employment in OECD countries, driven by a positive relationship within the services sector. Some evidence of a negative relationship between this IoT measure and industry employment was also found, in the full and the non-OECD samples. No evidence of a significant association between unemployment and IoT was found. The results are in line with the literature on technological change, and the idea that it creates winners and losers among workers. Nonetheless, any causal interpretation is beyond reach at this time.

Keywords: Internet of Things (IoT); Technological change; Employment; Unemployment; Labor; ICT.
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1 Introduction

The "Internet of Things" (IoT) has received, in recent years, a great deal of attention. Even though there is no unique, standard definition of IoT, we usually think of it as a network of "*smart devices*" with communication capabilities. The public attention has focused on consumer technologies, such as wearables and self-driving cars, and its implications for security and privacy. But there is also a wide-range of business and industrial applications that are often overlooked and make up the bulk of the potential value enabled by IoT. IoT technology enables devices and machines to communicate with each other, with the physical world, and over the internet using different technologies, such as mobile and fixed broadband, near-field communications, and radio-frequency identification. It is currently employed in numerous applications, from healthcare sensors to automated warehouses. The IoT will help firms in their transition to more automated tasks, but will also provide large amounts of data to help make better business decisions. While the number of IoT-connected devices has increased exponentially in the last decade, adoption across countries seems to suffer from the same *'digital divide'* that afflicted the early days of the internet. Yet, developing countries are starting to catch up to their wealthier counterparts.

Both consumer and business applications are expected to have an effect on the economy and employment, but while some research on the impact of IoT on economic growth has started to appear, its impact on the labor markets remains unexplored. Using data on cellular Internet of Things connections in a panel of countries, this thesis aims at investigating whether a significant relationship between IoT usage and employment outcomes exists. Therefore, the main research question this paper aims to answer is: *does the Internet of Things have an effect on the unemployment rate, total employment, or employment by sector?* This thesis contributes to the limited literature on the economic impact of the adoption of the Internet of Things. First of all, to the best of my knowledge, this is the first paper to investigate and provide any evidence on the relationship between IoT usage and labor outcomes. Secondly, within the literature on Information and Communication technologies (ICT), it provides new evidence on the effect of specific ICT applications on employment across countries.

Economists have long debated about the impact of technological change on labor demand. From a theoretical standpoint, how new technologies affect demand depends on their interaction with human labor, and the tasks and skills of workers affected. A general equilibrium effect is hence unclear. The empirical evidence supports this view: new tasks generated by technological change may displace some workers while generating increased demand for others. This impact also largely depends on the technology considered. Within the Information and Communication Technology (ICT) literature, ICTs such as broadband and Internet seem to have a strong positive contribution to growth and development (Bertschek et al., 2015), and productivity (Goodridge et al., 2019). The evidence on their impact on employment is also positive: broadband availability is associated with higher employment and population growth (Kolko, 2012), and has no impact on the unemployment rate (Czernich, 2014). Recent, although scarce, evidence on Internet of Things adoption points in the same direction of a positive effect: Edquist et al. (2021) and Espinoza et al. (2020) both find a positive impact of IoT investment across countries. Its relationship with labor outcomes, however, has not yet been tackled.

To explore this question, I construct a panel with more than 100 countries with data for cellular Internet of Things connections and economic statistics. The panel spans over the early years of IoT adoption (2010-2019). I use a two-way fixed effect Ordinary Least Squares estimation to test whether a significant relationship between the usage of IoT technologies and labor outcomes exists. I find a positive and significant association between Internet of Things connections per 100 inhabitants and the employment level only within OECD countries, and no relationship in the whole sample or non-OECD countries. This result seems to be entirely driven by increased employment in the services sector. Limited evidence of a negative relationship with industry employment in the other two samples was also found. No correlation between IoT connections and the unemployment rate was established, in any set of countries. In an attempt to establish a causal relationship, a system GMM dynamic panel estimator is used. However, no causal interpretation of the results can be made at this stage.

The rest of the thesis is organized as follows: section 2 provides background information on the Internet of Things, its applications and diffusion. Section 3 discusses previous literature on the effect of technological change, automation, information and communications

technology on jobs and labor demand, as well as that on the economic impact of IoT. Section 4 discusses the data and its sources. Section 5 describes the main empirical approach, whose results are presented in section 6. Section 7 tests the robustness of the main results. In section 8 further analyses are run. Section 9 discusses the results and limitations. Section 10 concludes.

2 Background

Since the introduction of the Internet, there has been an exponential increase in the number of devices connected. The number of mobile SIM cards has exceeded 10 billion worldwide in the second quarter of 2021, of which more than 5 billion are used in smartphones (GSMA, 2021). Each mobile subscriber has on average 1.5 SIM cards, and this number is expected to rise as consumers buy and use more and more devices. The phenomenon is, however, not limited to consumer products: new types of devices are emerging that allow machines to be connected to one another in industrial and business settings (Höller et al., 2014). In this scenario, it is useful to define a new paradigm, the *Internet of Things*.

2.1 Definition of IoT and Applications

There are a number of different definitions of the Internet of Things, and little consensus even within the Information and Communication Technology (ICT) literature[1]. The International Telecommunication Union (2012) refers to the Internet of Things as "A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies". The OECD (2016), instead, describes IoT as "an ecosystem in which applications and services are driven by data collected from devices that sense and interface with the physical world".

In this thesis I will refer to the Internet of Things as a network of interconnected *things*, or objects, with communication capabilities that can interact with each other, the physical world and over the Internet. These objects include, but are not limited to, devices

[1] According to the OECD (2011), "ICT products must primarily be intended to fulfil or enable the function of information processing and communication by electronic means, including transmission and display".

such as machines, computers, smartphones, and sensors that are capable of sending and receiving data. Data transmission can be based on different technologies, such as fixed telecommunications line protocols like Ethernet, wireless protocols including Radio-frequency identification (RFID), Near-field communication (NFC) and Wi-Fi, or cellular networks (European Commission, 2016). Höller et al. (2014) make a distinction between machine-to-machine communication (M2M) and the Internet of Things. In particular, Machine-to-machine connections allow communication between devices of the same type and a specific application; a common deployment of M2M communication is ATMs and point-of-sales terminals, besides industrial applications. While an IoT system includes machine-to-machine connections, it also allows for the broad sharing of data and connection of the devices directly to the Internet.

There is a wide range of industries and sectors in which IoT systems are employed. Well-known applications are consumer goods and electronics, like tablets, video game consoles, and smart watches, as well as smart home appliances such as internet-enabled refrigerators, washing machines, lights and thermostats. Despite the extensive publicity of consumer applications, Manyika et al. (2015) estimate that business-to-business uses can generate nearly 70 percent of potential value enabled by IoT. These uses can be found in healthcare, retail, industrial, transportation, and utilities settings. For instance, healthcare IoT solutions include remote health monitoring, in which wearable sensors that monitor oxygen or glucose levels transmit data from a patient to healthcare providers. The retail sector was among the first ones to be affected, introducing automated checkout, asset and inventory management systems in which items are often identified by RFID tags that are tracked and traced. The IoT is also essential to the deployment of autonomous or semi-autonomous machinery, including self-driving vehicles and advanced equipment. Self-driving vehicles are not only consumer-marketed cars but also industrial and public transport vehicles that can be self-driving or remotely controlled. Automated heavy machinery is currently employed in a diverse set of industries such as mining, construction, and deep-sea exploration. Other emerging applications include the smart grid, for the management of energy production, and the development of smart cities, where multiple urban infrastructures, such as utilities, heating and cooling, water, waste, and energy are integrated through IoT systems (Höller et al., 2014).

In general, the Internet of Things can help automate and monitor processes and tasks, such as the production of goods and delivery of services, which are common in different industries (Höller et al., 2014). However, the IoT is not only about automation: its systems are able to collect and share large amounts of high-quality data via the Internet, enabling businesses and governments to make better decisions. The collection of such data will then be important for Artificial Intelligence (AI) applications, which can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments (OECD, 2019). In this context, factories can use IoT sensors to constantly monitor machine performance and use AI applications on the data to schedule maintenance only when necessary, reducing downtime and maintenance costs, and extending the lives of machines (Hogan et al., 2016). For example, Volvo AB is currently using IoT data and artificial intelligence in its diagnostic services to predict maintenance issues and prevent breakdowns of its truck fleet (SAS, 2021).

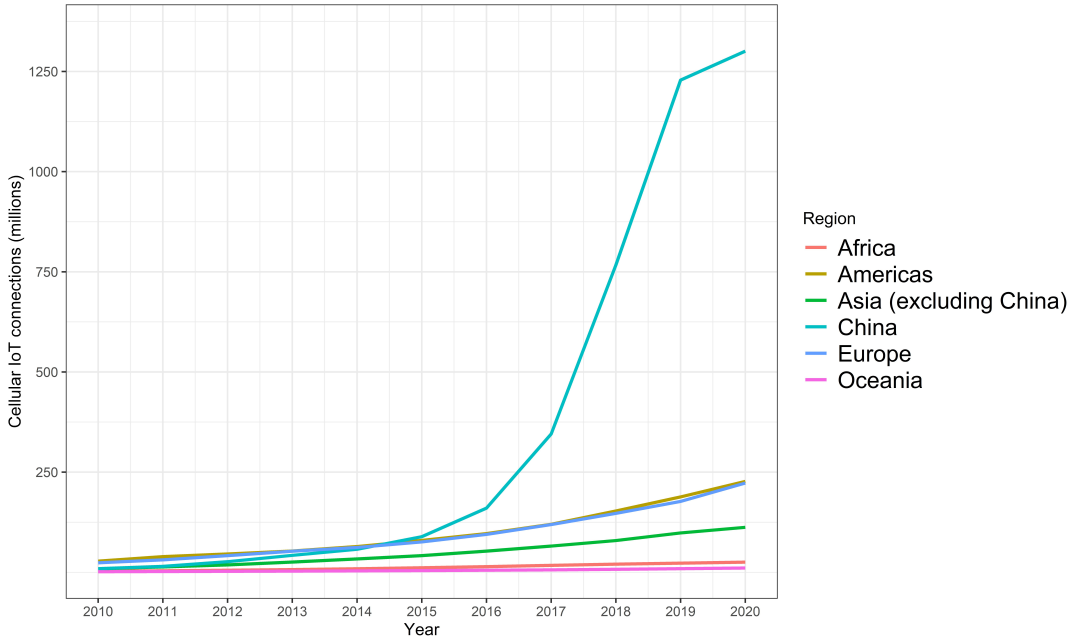
According to Fleisch (2010), a fundamental value driver of the IoT is that it eliminates real world-virtual world transaction costs. These so-called *'media breaks'* occur when information is transferred from one medium to another, such as from a bar code to a warehouse management system. The elimination of such transaction costs is central to the computerization of businesses and society: for instance, the introduction of accounting information systems allowed all data to be entered just once, reducing the error resulting from having all clerks manually transferring information from a piece of paper to a calculator and then back to paper (Fleisch, 2010). It is therefore important to take into account the ability of IoT systems to generate and distribute large volumes of data that is then utilized in different applications, in addition to its potential for automation.

2.2 Adoption and Diffusion of IoT

Despite the Covid-19 pandemic has forced many firms to put on hold their IoT projects, Kechiche et al. (2020) estimate that the Internet of Things market will be worth over $900 billion in revenue by 2025, from $348 billion in 2019. IoT connections will double to 24 billion by the same year. Figure 2.1 shows the number of cellular IoT connections between 2010 and 2020 by region[2].

[2]Unfortunately, data on the number of connections through other technologies is not available at the country-level.

Figure 2.1: Number of cellular IoT connections by region (2010-2020).



Source: Author's rendering of GSMA Intelligence Database (2021)

Figure 2.1 also shows the surge in the number of IoT connections in China since 2015. In 2020, China accounted for more than two thirds of the total number of cellular IoT connections, from 12.4% in 2010. The Chinese government has attached great importance to IoT, making it a national strategy as early as 2009 and promoting the development of IoT projects throughout the early 2010s (Li et al., 2018). Security and privacy regulations, which have hindered the diffusion of IoT in Western countries, are laxer in China, and Chinese consumers are less concerned about its implications (Kshetri, 2017). The large scale adoption of IoT in China cannot, however, be exclusively attributed to the efforts of the Chinese institutions. Kshetri (2017) argues that its large user base, the innovative achievement of its firms, in terms of IoT-related patents and products, and the technological expertise provided by multinationals all have played a role in China becoming the largest IoT market. According to Ryberg (2019), the Chinese market growth is driven by connected cars, payment terminals and industrial applications, and accelerated by government investment in surveillance and security systems and smart cities. There is, however, no data on each market segment's share of total connections.

Relative to its population, the number of IoT connections in China is still large. Table 2.1 shows the number of IoT connections per 100 inhabitants over time for selected countries, while figure 2.2 displays the distribution of connections per 100 inhabitants across the

world in 2020. Sweden is currently the leader in connections per capita: IoT systems are employed by government agencies in various applications, such as supervision of road and rail safety and maintenance (Lindman and Saarikko, 2019), and for the development of smart cities (Ahlgren et al., 2016), besides deployments in the private sector. There also seems to be a stark disparity in the levels of IoT connections per capita between developed and developing countries, proxied by membership status to the Organisation for Economic Co-operation and Development (OECD). This is in line with past evidence on what is now known as the *'digital divide'*, the cross-crountry disparity in terms of access to Internet and computers (Warschauer (2003); Chinn and Fairlie (2007)). Still, lower income countries have been catching up: in 2019, the average number of IoT connections in OECD countries was just 2.6 times that of non-OECD countries, down from a factor 10 in 2010.

Table 2.1: Number of IoT connections per 100 inhabitants for selected countries and regions

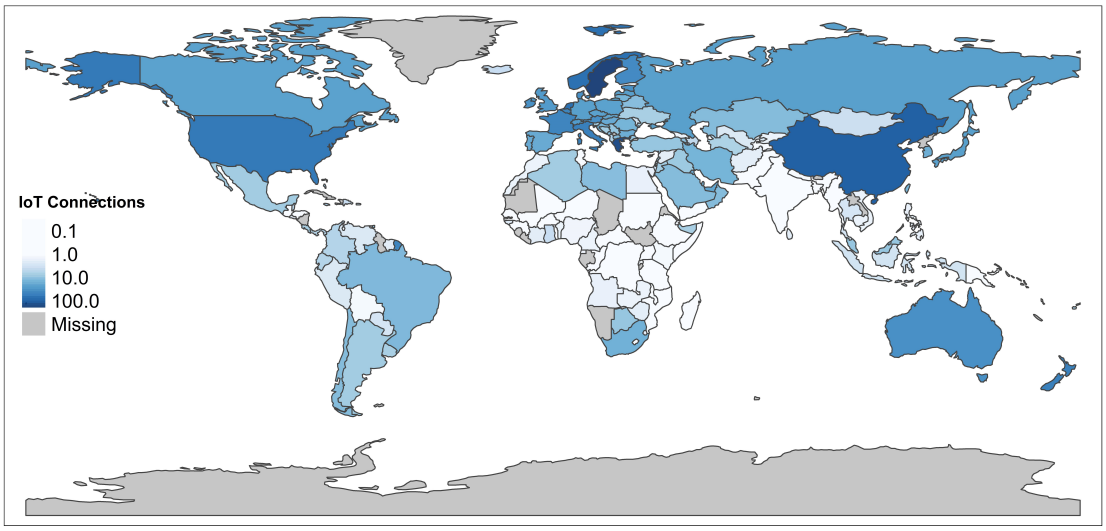
Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Australia	5.8	7.3	8.7	10.5	12.6	15.0	17.6	20.3	24.0	28.7	33.1
China	0.7	1.1	1.9	3.0	4.1	6.3	11.3	24.2	53.6	85.5	90.2
France	4.2	5.5	7.3	10.6	12.6	16.0	17.1	22.5	28.2	33.5	38.9
Germany	3.6	3.5	5.9	7.4	7.7	10.1	12.1	13.9	15.6	18.4	22.4
Italy	7.1	8.7	10.4	12.2	14.2	16.6	19.7	26.9	34.7	40.1	44.3
Japan	3.4	4.7	6.1	7.2	8.8	9.7	10.8	11.8	14.4	19.9	24.1
Netherlands	1.8	4.9	6.4	7.2	9.2	13.2	20.7	28.5	39.4	49.3	60.1
Sweden	21.4	28.3	37.5	49.9	58.5	64.4	83.2	111.0	125.1	146.4	176.2
U.K.	3.8	5.2	6.6	7.9	9.2	10.5	12.9	14.3	16.5	20.8	26.4
U.S.A	7.0	9.4	10.4	11.7	14.0	17.3	21.1	26.1	33.5	41.6	50.9
OECD	4.0	5.3	6.8	8.4	10.1	12.0	14.9	18.4	22.4	26.5	35.2
Non-OECD	0.4	0.7	1.3	2.5	4.2	5.5	7.9	9.5	11.0	12.5	13.5
World	1.1	1.5	2.3	2.5	3.1	4.1	5.6	8.9	15.3	22.2	24.2

Source: Author's rendering of GSMA Intelligence Database (2021)

2.3 IoT Deployment, Jobs and Skills

The Internet of Things, with its multitude of applications, is leading firms to become more and more automated, and provides them with high-resolution data. In their market survey of almost 2,900 enterprises, Kechiche (2020) find that businesses are deploying IoT both

Figure 2.2: Number of cellular IoT connections per 100 inhabitants by country in 2020.



Note: Logarithmic scale. *Source:* Author's rendering of GSMA Intelligence Database (2021)

to generate revenues and achieve cost savings, besides complying with new regulations. Hogan et al. (2016) and Sivakumaran (2019) find that IoT deployment leads to increased productivity, efficiency gains and cost reduction for businesses, and that the manufacturing sector will be the main beneficiary of these gains. While economic benefits for businesses are clear, the impact on jobs is less so. Automation through Internet of Things systems could potentially decrease the need for human labor. In particular, low-skilled, routine jobs may be at risk: for instance, with the advent of automated warehouse management, robotic deliveries, and self-driving vehicles, many warehouse workers, deliverymen, and drivers could be out of jobs. At the same time, the adoption of new technologies may increase the demand for high-skilled workers to develop and work on such technologies. Hogan et al. (2016) estimate that, in the U.K., the use of IoT and Big Data will foster business creation, which in turn will lead to job creation and increased employment. However, it may take some time for workers to acquire the skills needed in this new labor market, and it is hard to predict which effect will prevail.

On the other hand, consumer devices are mostly used for leisure (tablets, smart TVs), or to simplify everyday life (smart lights, home appliances). Consumer IoT will also likely have its own economic impact, which is however outside of the scope of this thesis.

3 Literature Review

This section summarizes previous academic literature on the impact of automation and technological change on jobs, by presenting a theoretical framework for potential channels, and the empirical evidence that supports these channels. It then focuses on the literature on Information and Communication Technologies and the Internet of Things and their effects on the economy and labor markets.

3.1 A Theoretical Framework

Since the Industrial Revolution, at the very least, workers have feared that new technologies might make their jobs obsolete. The Luddites, a group of textile workers, hand-loom weavers, and combers, worried they may become redundant, burned and destroyed the machinery that was threatening them (see Sale (1995) for a more detailed discussion). Economists have long discussed the effects of technological change on labor markets. According to Say (1836), while innovation and machinery can displace workers in the short term, machines themselves cannot be constructed without labor, thus generating new employment opportunities. Technological progress also leads to a reduction in prices, of which all consumers, including displaced workers, benefit. On the other hand, critics such as John Maynard Keynes, who coined the term *technological unemployment*, believed that unemployment resulting from labor-saving technologies would outpace the rate of new jobs creation (Keynes, 1933).

Following the task-based framework of labor demand developed in Acemoglu and Restrepo (2019), automation is defined as the adoption of new technologies that enable capital to be substituted for labor. It can affect labor demand through three channels. First, through the *displacement* effect: as automation enables capital to take over tasks previously performed by labor, the labor share of value added and the demand for labor decrease. Secondly, through the *productivity* effect, automation increases productivity by allowing a more flexible distribution of tasks between labor and capital, contributing to the demand for labor in non-automated tasks. Lastly, the *reinstatement* effect describes the establishment of new tasks in which labor has a comparative advantage, positively contributing to the labor share of value added and demand for labor. The displacement and reinstatement effects

are then antipodes: going back to the Luddites, the mechanical loom may have displaced weavers while simultaneously creating demand for loom-repairmen. The equilibrium effect on aggregate demand for labor hence depends on how new technologies allocate tasks across factors of production and which channel dominates. Applying the framework to U.S. data, they find a slowdown in the growth of labor demand since 1987, which can be explained by a strong displacement effect, driven by the expansion of automation, and a weaker reinstatement effect resulting from a slower adoption of labor-reinstating technologies and tasks.

Empirical evidence supports the framework and its channels: Karabarbounis and Neiman (2014) find that, globally, half of the decrease in labor share of income can be explained by a lower price of investment goods, attributed to advancements in computers and information technologies. Brynjolfsson and Hitt (2003) find both short- and long-term increases in productivity and output to be associated with computerization at the firm-level between 1987–1994. Finally, Autor et al. (2003) find that computerization leads to a shift in tasks from routine manual and cognitive tasks, in which computer capital can substitute workers, to nonroutine cognitive tasks, in which it cannot. There are various and extreme estimates of the share of jobs that are at risk to be automated: Frey and Osborne (2017) look at the risk of computerization of more than 700 occupations and find that 49% of U.S. jobs could be automated within a decade or two. Looking at single tasks, rather than occupations, Arntz et al. (2016) estimate that 9% of all jobs within OECD countries are automatable, with some variation across countries. While Acemoglu and Restrepo (2019) abstract from the skill levels of workers, Acemoglu and Restrepo (2020) expand the task-based framework to include different skills among workers. Using U.S. industry data, they show that displacement driven by automation is significantly associated with an increase in the demand for skills. Reinstatement of workers due to new tasks is instead associated with reduced demand for skills before 1987 and increased demand for skills after 1987, depending on what skill level had a comparative advantage in the new tasks generated.

As mentioned in section 2, the Internet of Things can help automate processes and tasks, and can then be analyzed in light of this framework. However, the Internet of Things is not only automation: the ability to collect data from the real world, and to share

it over the Internet, is an essential characteristic of IoT systems. The IoT has then the potential to provide large amounts of data to firms and enterprises to help them make business decisions. According to Edquist et al. (2021), IoT can be considered a complementary innovation based on Information and Communication technology (ICT), much like the the electric motor was complementary to wider electrification. Bresnahan and Trajtenberg (1995) define General Purpose Technologies (GPTs), such as the steam engine and electricity, as key technologies in economic growth. They are characterized by the potential for pervasive use in a wide range of sectors that generate and enable spillovers and new opportunities for innovation, what they call 'innovational complementarities'. Due to its use in a wide range of industries and applications, ICT has been classified as a GPT (see O'Mahony and Vecchi (2005), Venturini (2009), Venturini et al. (2013)). It is then appropriate to explore the literature on the economic impact of ICT as well.

3.2 Evidence on the Adoption of ICTs

There is extensive literature on the impact of telecommunications on economic growth and productivity (see for instance Oliner and Sichel (2000); Jorgenson et al. (2008); O'Mahony and Vecchi (2005); Roller and Waverman (2001); Van Ark et al. (2008)). Investment in telecommunications infrastructure, such as fixed line and mobile broadband, has contributed significantly to income growth and regional development (see Bertschek et al. (2015) and Vu et al. (2020) for surveys on the empirical evidence on economic growth). Similarly, Goodridge et al. (2019) find evidence of a robust correlation between ICT capital services and total factor productivity (TFP) growth in Europe and the U.S., with a stronger effect in the U.S.

Within the ICT literature, the empirical evidence on the impact on employment is mixed, and much of the research on labor outcomes employs microdata on broadband availability or adoption. Kolko (2012), for instance, uses ZIP code and county-level U.S. data and finds that a higher number of broadband providers positively impacts employment and population growth, and the effect is stronger in industries that rely more on IT and in areas with lower population densities. Crandall et al. (2007) provides an early analysis on the impact of broadband penetration on output and employment using U.S. state-level data, and find that employment is positively and significantly associated with broadband

use, though no causal link can be established. Atasoy (2013) find comparable results: at the county-level, gaining access to broadband through federal policy programs is associated with an increase in the employment rate, as a result of increased labor demand from existing firms. In Europe, Czernich (2014) find that broadband internet availability in German municipalities has no impact on the unemployment rate.

Cross-country analyses of these relationships are instead less common, due to limited data availability. Biagi and Falk (2017) focus on different ICT activities and e-commerce using firm-level data from ten European countries, and find ICT applications to be overall neutral to employment. O'Mahony et al. (2008) compare the impact of ICT capital on the demand for skilled labor in the U.S., the U.K. and France. They find strong evidence of capital-skill complementarity for the highest skill groups and of capital-skill substitution for the intermediate skill groups, while mixed evidence for the lowest skill groups.

Large part of these results points in the same direction, however in most cases they cannot be interpreted as evidence of a causal effect. There is also evidence that the overall economic impact of ICT technologies largely depends on which technology is considered, and there is a differential effect between developed and developing countries (Stanley et al., 2018).

3.3 Evidence on the Adoption of IoT

Besides the market and policy research described in section 2.3, there is limited academic research on the economic impact of the Internet of Things, and it is mostly focused on the effect on productivity and growth. Edquist et al. (2021) explore the impact of IoT technologies on economic growth. Using early data for 82 countries on cellular IoT connections, they find a strong and significant correlation between the change in IoT and total factor productivity growth: a 10 percentage points increase in the growth of IoT connections is associated with a 0.23 percentage points increase in TFP. They then use a growth-accounting approach for longer run predictions and estimate total contribution of IoT investment to growth between 0.01% and 0.99% per annum (2018-2030). Espinoza et al. (2020) use the same growth-accounting approach and find a positive, yet small, impact of the IoT on productivity at its early stage of development.

There are, at the time of writing this thesis, no empirical studies on the relationship between Internet of Things usage and labor outcomes. Given that an impact on productivity and economic growth has already been detected in a cross-country setting by Edquist et al. (2021), it is possible that spillovers on the demand for labor inputs have occurred. Some very limited evidence at the firm-level is starting to appear. Balsmeier and Woerter (2019) explore the influence of digitalization on jobs creation in Swiss firms across skill levels. Using representative survey data on technologies adoption in the private sector, they find that investment in digitalization is associated with higher employment of high-skilled workers and lower employment of low-skilled workers, and the effect is driven by firms that employ machine-based digital technologies, including IoT. However, their measure of investment in digitalization is broadly defined, and the distinction between firms that employ machine-based digital technologies and those which don't is based on the adoption of a wide-range of technologies, including robots, 3D printing and IoT. It is therefore impossible to disentangle IoT from other innovations. In a working paper, Kariel (2021) looks at firm-level theory and evidence on employment and productivity of different automation technologies, including the Internet of Things. Through an event study of Italian firms, the author finds a rise in employment and hours worked and in the years following IoT adoption, among adopters. Still, this only provides evidence on the introduction of IoT within a firm, and not on the intensity of usage. Together, these two results point towards the direction of a positive relationship of IoT adoption and employment at the firm level, but not conclusively so.

4 Data

This section describes the data used in the econometric analysis and its sources. All variables are measured at the country-level.

4.1 Independent Variable

The independent variable of interest is Internet of Things usage, or penetration. Currently, no data on IoT investment or capital equipment is available or can be estimated at the country-level, however the number of mobile IoT connections is available. Following Edquist et al. (2021), I employ the number of IoT connections over 100 inhabitants as a

proxy, which allows for cross-country comparisons. Nevertheless, since the aim here is to identify a relationship between IoT usage and labor outcomes, it makes intuitive sense to relate this measure of IoT equipment, i.e. the number of IoT connection, to population size.

The data on the number of Internet of Things connections and country population size comes from the GSMA Intelligence Database, which collects industry data from mobile operators. The GSMA Intelligence database describes IoT connections as *"Total unique SIM cards that have been registered on the mobile network at the end of the period enabling mobile data transmission between two or more machines via cellular M2M (2G, 3G, 4G or 5G) or Low-Power Wide-Area (LPWA) technologies. Licensed cellular IoT excludes computing devices in consumer electronics such as e-readers, smartphones, dongles and tablets"* (GSMA, 2021). The database starts recording the number of IoT connections in a country from the year mobile operators started offering M2M/LPWA services in that country. Observations for previous years are therefore denoted as missing values, while the real meaning behind these initial missing values is that no IoT connections were available in the country or they were too few to be recorded. I thus replaced initial missing values with zeroes.

As discussed in section 2.3, consumer IoT is outside of the focus of this thesis. Moreover, the bulk of connected devices is in non-consumer devices (European Commission, 2016), and consumer IoT mainly relies on Ethernet and Wi-Fi (Höller et al., 2014). There is currently no data on the number of IoT devices connected through technologies other than cellular, so the assumption is that they follow similar patterns in terms of penetration and economic impact. Nevertheless, there are still reasons to choose mobile infrastructure, and in particular LPWA, relative to other technologies, as it is safer to security threats, more reliable and allows communication over greater distances (Sinha et al., 2017).

4.2 Dependent Variables

4.2.1 Unemployment Rate

The unemployment rate is defined as the number of unemployed persons over 15 years of age as a percentage of the total number of persons in the labor force, and is provided

by the International Labour Organization's *ILOSTAT* database. The data includes the observed unemployment rate collected by national authorities and ILO modelled estimates when not available (International Labour Organization, 2021)[3]. As a robustness check, in section 7, the unemployment level is used instead of the unemployment rate, also from the *ILOSTAT* database. While the unemployment rate is harmonized in its definition and comparable across countries, it is also a volatile indicator of the labor market and is very sensible to business cycles (Pissarides (2009); Romer (1986)). I will then also employ total employment as a dependent variable, which is generally less volatile.

4.2.2 Total Employment

Total employment is provided by the the Conference Board's *Total Economy Database*, and is defined as *all persons engaged in some productive activity that fall within the production boundary of the system of national accounts (employees, self-employed, unpaid family workers and the military)*. To further try to identify the differential impacts of the Internet of Things in different sectors, I will also divide total employment in three different sectors: *Agriculture, Industry, and Services*, by multiplying the total number of people engaged with the share of employment in each sector. Employment by sector as a share of total employment is available from the World Bank's *World Development Indicators database* and is sourced from the International Labour Organization, ILOSTAT database. Table 4.1 provides a description of which activities are included in each sector.

It is also possible to distinguish between the intensive and extensive margin of labor supply. The extensive margin, total persons engaged, and the intensive margin, hours worked per worker, have had diverging trends over time since the 1970s in OECD countries (Rogerson, 2006). Firms in different countries also have different incentives to adjust labor input along the extensive and the intensive margin depending on the labor market institutions in case of a shock (see Ohanian and Raffo (2012) and Bulligan et al. (2019)). However, hours worked per worker change very little over time, due to cultural differences, institutional constraints and regulations in national labor markets. For instance, Rogerson (2006) finds that hours worked in Germany decreased by around 30% in the 50 years between

[3]According to the International Labor Organization, modelled estimates carry a high degree of uncertainty for countries with limited official data. For this reason, I additionally estimated the econometric analysis excluding modelled estimates. The results were comparable, so I will only include estimations based on the balanced panel that includes ILO estimates.

Table 4.1: Description of employment by sector

Sector	Description
Agriculture	Agriculture; hunting; forestry; fishing.
Industry	Mining and quarrying; manufacturing, construction; public utilities: electricity, gas, and water.
Services	Wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; community, social, and personal services.

Source: World Bank (2021)

1955 and 2005, while Anglo-Saxon countries like the U.S., Canada and Australia in turn experienced a modest increase during the same time. It is therefore extremely hard to detect any effect due to new technologies, and especially in a short time frame. Given the limited time period of my data and the scarce availability of country-level data on hours worked per worker, I decided to estimate the relationship between IoT and employment exclusively across the extensive margin.

4.3 Control Variables

Throughout the analysis, several control variables are used. Section 5 discusses in greater detail the reasoning behind the inclusion of each control variable in the model. Here is a brief description of each variable and its source.

A few macroeconomic indicators are included. Real GDP per capita in 2020 international dollars, converted using Purchasing Power Parities, comes from Conference Board's *Total Economy Database*. The inflation rate, from the *World Development Indicators database*, is measured as annual growth rate of the GDP implicit deflator, and shows the rate of price change in the economy as a whole. A measure of international trade is also introduced. It is defined as the sum of imports and exports of goods and services as a share of Gross Domestic Product, and is from the World Bank's *World Development Indicators database*.

Country-level demographic variables taken into account are the human capital index, population density and working age population. The human capital index is taken from

the Groningen Growth and Development Centre's Penn World Table version 10.0, and is constructed based on average years of schooling and returns to education (Feenstra et al., 2015). Population density is defined as total population (from the GSMA Intelligence Database) divided by land area in squared kilometers (from the World Bank's *World Development Indicators database*). The working-age population is defined as the share of the population between the ages of 15 and 64 (from the World Bank's *World Development Indicators database*) times total population.

Finally, two ICT measures are included. Mobile broadband connections are defined as total unique SIM cards (or phone numbers, where SIM cards are not used) excluding cellular IoT connections and come from the GSMA Intelligence database. Data on fixed broadband subscriptions comes from the International Telecommunications Union (ITU) World Telecommunication/ICT Indicators database[4]. The ITU describes fixed broadband subscriptions as *"subscriptions to high-speed access to the public Internet, and includes cable modem; DSL; fibre-to-the-home/building; other fixed (wired)-broadband subscriptions; satellite broadband and terrestrial fixed wireless broadband. It excludes subscriptions that have access to data communications (including the Internet) via mobile-cellular networks, and includes both residential subscriptions and subscriptions for organizations"* (International Telecommunication Union, 2021). Both mobile and fixed broadband connections or subscriptions are used in the analysis as per 100 inhabitants[5].

4.4 Final Data

A panel of 107 countries and territories[6] over ten years, from 2010 to 2019, is constructed. It includes 36 OECD countries and 71 non-OECD countries; a full list of countries in the sample can be found in appendix A. Some countries have become full OECD members within the years considered in the panel: Chile, Slovenia, Israel and Estonia obtained full membership in 2010; Latvia in 2016 and Lithuania in 2018. I will consider as OECD

[4]One exception is New Zealand in 2019, which is not available and is replaced with the value from the OECD Broadband database (2019 Edition). Since the data is provided to the ITU by New Zealand's Ministry of Business, Innovation and Employment as it provided to the OECD, the 2019 measure is comparable to earlier ones.

[5]Variables that are relative to population size (i.e. IoT connections, mobile broadband connections, fixed broadband subscriptions, population density, working age population) were computed using the same estimate for population size, with the exception of per capita GDP, which is used as is from the original source.

[6]I will refer to them generally as countries, even though not all of them are sovereign states.

countries all those which were full members as of 2019, independently of the year they obtained full membership. The panel is slightly unbalanced as not all control variables are available for each year and country. In particular, the measure of trade and the number of fixed broadband subscriptions are missing for 2 and 17 year-country observations respectively.

Table 4.2 shows descriptive statistics of the variables of interest for the full sample, while table A.1 divides the sample between OECD and non-OECD countries. All variables show sufficient variation, both across countries and over time.

Table 4.2: Descriptive statistics for the full sample (2010-2019)

	Mean	St. Dev.	Min	Max	N
Unemployment rate (in %)	7.15	5.03	0.11	28.47	1,070
Unemployment (in thousands)	1,613	4,502	2	37,112	1,070
Employment (in thousands)	27,442	87,540	163	762,101	1,070
Employment in Agriculture (in thousands)	7,901	30,932	1	278,797	1,070
Employment in Industry (in thousands)	6,434	24,109	30	230,629	1,070
Employment in Services (in thousands)	13,107	35,441	120	355,838	1,070
Working-age population (in thousands)	41,636	129,489	216	1,024,188	1,070
IoT connections*	6.08	11.02	0	146.37	1,070
Per Capita GDP	26,956	24,073	813	120,408	1,070
Population Density	293.01	1,012.41	2.60	8,219.10	1,070
Inflation rate (in %)	5.13	12.84	-25.96	350.00	1,070
Trade (% of GDP)	91.27	65.53	16.14	442.62	1,068
Human Capital	2.74	0.68	1.17	4.35	1,070
Total mobile connections*	114.27	35.65	9.68	202.10	1,070
Fixed Broadband subscriptions*	15.34	13.77	0	46.65	1,053

*Connections and subscriptions expressed per 100 inhabitants.

5 Empirical Approach

5.1 Two-way Fixed Effects Estimation

Czernich et al. (2011) find two channels through which high-speed internet access via mobile broadband can affect economic growth: its introduction in a country and its penetration rate, measured as the share of the population that has subscribed to broadband. Ideally, one would similarly exploit the roll out of IoT connections in a difference-in-differences specification to estimate whether its introduction had a one-time effect on labor

outcomes. Unfortunately the data on IoT connections is only available from 2010, when IoT connections had already reached 1% of total cellular (IoT and other) connections worldwide and values as high as 13% in Sweden and 8% in Norway.
For this reason, I will focus on the penetration of the Internet of Things, defined as the number of licensed cellular IoT connections per 100 inhabitants, in a two-way fixed effect OLS estimation with continuous treatment.

First, to estimate the relationship between IoT penetration and unemployment, I will regress the unemployment rate on IoT penetration using the following specification:

$$UnemploymentR_{it} = \beta_0 + \beta_1 IoT100_{it} + \gamma K_{it} + a_i + a_t + \varepsilon_{it} \tag{5.1}$$

where $UnemploymentR_{it}$ is the unemployment rate in country i in year t, $IoT100_{it}$ is the number of licensed IoT connections per 100 inhabitants, K_{it} is a vector of country-level controls, a_i captures country fixed effects and a_t are year fixed effects. The vector of control variables K_{it} includes log GDP per capita, the inflation rate, the Human Capital Index, population density, the number of fixed broadband subscriptions per 100 inhabitants and of mobile broadband connections, other than IoT connections, per 100 inhabitants. In terms of control variables, I made a number of choices over which controls to include following economic theory and previous empirical literature on the impact of ICTs. The economic development of a country, proxied by GDP per capita, could likely be determining both the unemployment rate and the usage of IoT technologies. Inflation is included to account for a Phillips curve type of relationship with the unemployment rate (Phillips, 1958). Trade as a percentage of GDP is included to account for the effect of trade shocks and import competition on the labor market of a country (see Autor et al. (2014), Autor et al. (2016) and Acemoglu et al. (2016) for an in-depth discussion on the topic). Population density controls for the "thickness" of the labor market over time, as job-seekers in densely populated areas have a higher chance of finding a match with an employer (Moretti, 2011). Following Crandall et al. (2007), who study the relationship between broadband deployment and employment within the U.S., a higher human capital index implies higher education of the people in a country and should create a favorable business climate for businesses and higher demand for labor, bringing down unemployment. Crandall et al. (2007) also include union membership rates across U.S. states, however there is limited

data available on country-level union rates for recent years.

Fixed and mobile broadband connections per 100 inhabitants are included to make sure that the number of IoT connections is not just picking up the usage of broadband in a country, which has its own impact on labor outcomes (see Bertschek et al. (2015); Atasoy (2013); Jayakar and Park (2013)). Including the number of fixed broadband subscriptions can also partly control for the fact that the number of IoT devices connected through fixed broadband technologies, such as Wi-Fi, is not available. Given that cellular IoT relies on the same technology and infrastructure as mobile broadband, it could be argued that the number of mobile broadband connections is a bad control in this particular regression. According to the definition by Angrist and Pischke (2008), *"[...] Bad controls are variables that are themselves outcome variables in the notional experiment at hand. That is, bad controls might just as well be dependent variables too. Good controls are variables that we can think of as having been fixed at the time the regressor of interest was determined. [...] A second version of the bad control scenario involves proxy control, that is, the inclusion of variables that might partially control for omitted factors, but are themselves affected by the variable of interest."*. Neither version of bad controls seems to be the case here. Conversely, mobile broadband infrastructure had largely already been determined by the introduction of IoT; while some improvements (e.g. 4G and 5G technologies) have been introduced in the panel of years considered, advancements in the technology are mostly carried out upgrading or modifying the pre-existing cellular infrastructure (Edquist et al., 2018).

Including country fixed effects accounts for unobservable time-invariant, country-level factors that affect the outcome of interest, for instance slow-changing cultural and institutional factors that determine long-term labor market outcomes. Given the short time span of the panel, I did not control for any institutional or labor market characteristics, which are going to be reflected in country fixed effects. Labor market policies and structural reforms take time to be implemented, and for their effects to materialize (see for instance Bouis et al. (2012)). On the other hand, year fixed effects instead account for unobservable factors that vary across time but are common to all countries, such as global economic trends and downturns. The coefficient of interest is β_1, the OLS estimator, which shows the change (in percentage points) of one additional IoT connection per 100

inhabitants on the unemployment rate, ceteris paribus.

As mentioned earlier, the unemployment rate is a rather volatile measure of the labor market in a country. Besides, the unemployment rate, defined as the number of people who are not currently employed but are looking for a job as a percentage of the labor force, overlooks the number of *discouraged workers*, those who are neither employed nor seeking employment. If the Internet of Things displaced workers in certain occupations and these workers dropped out of the labor force, discouraged that they would not be able to find a new job, this would not be reflected in specification 5.1. Therefore, I will use total employment as an alternative dependent variable, which is a more stable measure of the labor market. A second specification will be estimated as follows:

$$Log(Employment_{it}) = \beta_0 + \beta_1 IoT100_{it} + \gamma X_{it} + a_i + a_t + \varepsilon_{it} \tag{5.2}$$

Moreover, it could potentially be the case that total employment is measured at a too aggregate level to detect any effects, or that IoT has opposite effects on different sectors of the economy, which balance out at the macro level. For these reasons, I will estimate a third specification:

$$Log(Employment_{it,j}) = \beta_0 + \beta_1 IoT100_{it} + \gamma X_{it} + a_i + a_t + \varepsilon_{it} \tag{5.3}$$

where $Log(Employment_{it,j})$ is the log form of the total number of people employed in country i in year t, and $Log(Employment_{it})$ is the log form of the total number of people employed in country i in year t in sector $j \in \{Agriculture; Industry; Services\}$. The vector of controls X_{it} is defined as in 5.1, plus the logarithm of working age population, to control for the growth in the labor force. In the last two specifications the coefficient of interest β_1 can be interpreted as the expected change in log Employment (either total or by sector): a 1 unit increase in the number of IoT connections per 100 inhabitants is associated with approximately a $(\beta_1 * 100)\%$ change in the employment level, holding everything else constant.

While Edquist et al. (2021) find similar results for the relationship between TFP growth and IoT connections across countries, in the ICT literature there is evidence of a differential effect of telecommunications across high- and low- income countries on GDP growth and

productivity (see Waverman et al. (2005); Lam and Shiu (2010); Thompson Jr and Garbacz (2007); Roller and Waverman (2001); Edquist et al. (2018)). Thus, I will estimate the two specifications separately for the two samples of OECD and non-OECD countries, in addition to the full sample. Of course, a distinction between high- and low-income, or more or less developed, countries based on whether one is a full member of the OECD is just as arbitrary as any. Nonetheless, this allows the results to be comparable to previous ICT literature.

When dealing with panel data, there are different estimations that allow to remove unobserved fixed effects. I have chosen to use a two-way fixed effects estimation, which removes the unobserved effects by subtracting the time-averaged value of each dependent, independent and control variable from the model, within a country. It then effectively explains the variation around the mean of the independent variable in terms of variation around the mean of the variables on the right hand side, and removes all time-invariant unobserved factors that could bias the estimate of the coefficient of interest. An alternative to the fixed effects model would be a random effects model, which subtracts only a fraction of the time-average values of each variable. However, it relies on the assumption that the unobserved effect is independent of all explanatory variables in all time periods (Wooldridge, 2015), which I deem not to be the case here. Nevertheless, it is also possible to use a Hausman (1978) specification test for fixed versus random effects. Under all specifications estimated, the hypothesis that the country fixed effects are adequately modeled by a random effects model was rejected, and therefore only fixed effects estimations are presented.

Finally, it is worth discussing the approach to standard errors. Within all specifications, standard errors are clustered at the country level, to account for potentially serially correlated errors across years for a given country, given that there are enough clusters (Bertrand et al., 2004).

5.2 Limitations

One problem with dividing total employment in the three different sectors (equation 6.3) is that the dependent variable, IoT connections per 100 inhabitants, is the aggregate

measure of IoT penetration in a country and cannot be disaggregated into sectors. This will introduce measurement error and the coefficient obtained will be biased, in its magnitude, relative to the true one. Still, the results, if any, will be informative of at least the direction of the relationship.

While one must always be careful when interpreting any effect as causal, the specifications outlined above are likely to suffer from endogeneity. In this case, one obvious threat to a causal identification is simultaneity bias. As labor gets more expensive, when the employment level is high, firms may in turn decide to invest more intensively in machinery, automation, and in the Internet of Things in order to reduce their labor costs. The specifications are also potentially subject to omitted variable bias: there may be unobservable time-varying factors, correlated with the number of IoT connections that determines the employment level. If this is the case, the coefficient of interest, β_1, will be biased.

One way to address possible endogeneity concerns described above is to use an instrumental variable (IV) to debias the coefficient. An instrumental variable approach works by using a third variable that affects the dependent variable only through the independent variable of interest. Currently, no suitable instrument has been identified within the literature on the economic impact of IoT. In the wider literature on Information and communication technology, multiple instruments have been used to identify causal effects of mobile broadband and internet access. Many of them build on prior infrastructure and technologies on which mobile broadband relies on. For instance, Edquist et al. (2018) model the maximum penetration level of mobile broadband as a linear function of the diffusion of mobile phone infrastructure (cellular telephone subscriptions per 100 inhabitants in 2002) and personal computers (fixed Internet subscribers per 100 inhabitants in 2002) before the diffusion of mobile broadband. Kolko (2012) instruments broadband availability with the slope of terrain, while Czernich (2014) uses distance from the main distribution frame, i.e. the cable rack to which each individual household's fibre is connected. None of them appear to be relevant in this case.

While cellular IoT technology builds on pre-existing mobile broadband networks, this is not a suitable instrument since mobile broadband is likely to have an effect on economic development and employment on its own (see Prieger (2013)). I have attempted to find a

possible instrumental variable that exploits the exogenous variation in my independent variable. In particular, by instrumenting IoT connections with 5th generation (5G) broadband network connections. The instrument appeared to be relevant, as data transmission between machines can occur either via cellular networks (3G, 4G, or 5G) or via LPWA, which can't be used by 3G and 4G technologies (Chettri and Bera, 2020). While the instrument is unlikely to be completely exogenous, the exclusion restriction could potentially hold since IoT connections exclude smart devices, such as smartphones, tablets and dongles. Thus, the only channel through which the number of 5G connections may have an impact on employment is through the Internet of Things and machine to machine data transmission outside consumer electronics. This was true up to 2020, since 4G devices are not able to use 5G networks, and the first commercial 5G applications, such as smartphones, only started to become available in 2020. Nevertheless, I cannot run such as estimation since data on 5G connections is only available for two years before 2020 and only for a handful of countries. While the IV estimator is consistent, it is still biased in finite samples and needs asymptotic justification. Therefore, it is not a viable option.

A second way to address potential endogeneity, when an external instrumental variable is not available, is to use dynamic panel data models. This approach is explored in section 8.

6 Main Results

6.1 Anticipatory Effects

In order to trust the results the two-way fixed effects OLS estimation, I first run a Granger causality-type test as proposed by Angrist and Pischke (2008). The idea is to make sure that Granger-causality runs from Internet of Things connections and not vice versa, i.e. past levels of IoT connections may predict the dependent variable, while future ones may not, conditional on country and year fixed effects and the control variables. I test this by estimating the specifications outlined in section 5 with lags and leads of the independent variable. Given the restricted time span of my panel, I chose to include two lags and one

lead:

$$UnemploymentR_{it} = \beta_0 + \beta_1 IoT_{it-2} + \beta_2 IoT_{it-1} + \beta_3 IoT100_{it} \\ + \beta_4 IoT_{it+1} + \gamma K_{it} + a_i + a_t + \varepsilon_{it} \tag{6.1}$$

$$Log(Employment_{it}) = \beta_0 + \beta_1 IoT_{it-2} + \beta_2 IoT_{it-1} + \beta_3 IoT100_{it} \\ + \beta_4 IoT_{it+1} + \gamma X_{it} + a_i + a_t + \varepsilon_{it} \tag{6.2}$$

$$Log(Employment_{it,j}) = \beta_0 + \beta_1 IoT_{it-2} + \beta_2 IoT_{it-1} + \beta_3 IoT100_{it} \\ + \beta_4 IoT_{it+1} + \gamma X_{it} + a_i + a_t + \varepsilon_{it} \tag{6.3}$$

where the dependent variable and the regressors are defined as before, i indexes the country and t the year. If IoT connections Granger-cause employment or unemployment, future values of the treatment in a country should not matter for employment or unemployment, and β_4 should not be statistically significantly different from zero. If this does not hold, we may observe anticipatory effects. This would be the case if, for instance, firms within a country started firing or employing workers based on their future plans for the implementation of IoT solutions. While it is a useful check for the model at hand, Granger causality alone is not sufficient for causal inference (Angrist and Pischke, 2008).

Table 6.1 reports the results of this test. There seem to be no anticipatory effects for the unemployment rate and total employment. Looking at employment by sector, there seems to be some evidence of anticipatory effects of IoT within employment in agriculture and industry. Therefore, the estimates provided by these two specifications may be biased and unreliable, though the coefficients on the two one-year lead are only significant at the 10% level, which suggests that the relationship is not very strong or robust. Within employment in services, instead, only the coefficients on lagged independent variables are significant. Table B.1 in the appendix runs the same estimation, splitting the sample into OECD and non-OECD countries. The conclusion is the same.

Table 6.1: Granger causality-type test

			Log Employment in sector:		
	(1) UnemploymentR	(2) LogEmployment	(3) Agriculture	(4) Industry	(5) Services
IoT100_{t-2}	-0.133	0.000898	0.00718	-0.00304	-0.00527**
	(0.0805)	(0.00173)	(0.00495)	(0.00296)	(0.00240)
IoT100_{t-1}	0.0525	0.000575	-0.00326	0.00269	0.00281**
	(0.0598)	(0.00122)	(0.00358)	(0.00225)	(0.00124)
IoT100_{t}	-0.0370	-0.000384	-0.00215	-0.000413	-0.00106
	(0.0353)	(0.000711)	(0.00190)	(0.00156)	(0.000772)
IoT100_{t+1}	0.0474	-0.000567	0.00191*	-0.00159*	0.000764
	(0.0309)	(0.000419)	(0.00103)	(0.000915)	(0.000775)
Constant	104.0***	8.308***	5.904*	3.638***	6.308***
	(22.77)	(0.893)	(3.039)	(1.228)	(0.933)
Sample	Full	Full	Full	Full	Full
Number of countries	107	107	107	107	107
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	741	741	741	741	741
R-squared	0.291	0.577	0.128	0.452	0.688
F-test (p-value)	7.87e-07	0	6.01e-05	0	0

Notes: Cluster Robust standard errors in parentheses. ***$p<0.01$,** $p<0.05$,* $p<0.1$

6.2 Two-way Fixed Effects Estimation

The results from the estimation of specification 5.1 are presented in table 6.2, with the unemployment rate as dependent variable. Columns (1) and (2) show the relationship between the unemployment rate and the number of cellular IoT connections per 100 inhabitants in the full sample with and without controls, respectively. Columns (3) and (4) estimate the model with controls separately for OECD and non-OECD countries. The estimated coefficient of interest β_1 is not significantly different from zero in any of the samples. None of the specifications show any significant association between the unemployment rate and the number of Internet of Things connections in a country at either the 5% or 1% significance level.

Table 6.3 shows the results from the estimation with (log) total employment as dependent variable. Column (1) shows a negative and significant, at the 5% level, raw correlation between employment and IoT connections in the full sample. This association turns insignificantly different from zero after controlling for additional covariates such as working-

Table 6.2: Main results, unemployment rate

	(1) UnemploymentR	(2) UnemploymentR	(3) UnemploymentR	(4) UnemploymentR
IoT100	-0.0241	-0.0141	0.00377	0.0195
	(0.0154)	(0.0181)	(0.0109)	(0.0169)
Constant	7.674***	96.80***	337.9***	57.39***
	(0.212)	(22.85)	(64.49)	(14.66)
Sample	Full	Full	OECD	Non-OECD
Number of countries	107	107	36	71
Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	1,070	1,051	360	691
R-squared	0.109	0.254	0.698	0.124
F-test (p-value)	1.28e-06	0.000268	0	0.00751

Notes: Cluster Robust standard errors in parentheses. $^{***}p<0.01$,$^{**}p<0.05$,$^{*}p<0.1$

age population, GDP, trade, inflation, human capital, population density and mobile and fixed broadband connections (column (2)). There is, instead, a positive correlation when estimating the relationship in the OECD sample alone, which is significantly different from zero at the 1% significance level. The coefficient resulting from column (3) implies that one additional IoT connection is associated with approximately a $\beta_1 * 100 = 0.059\%$ ($p = 0.003$) increase in the employment level in a country, ceteris paribus, within OECD members. It should be noted that in the years considered, the 10-year average number of IoT connections per 100 inhabitants was 12.9 in the OECD sample, and grew, on average, by 2.3 connections per year. A one-unit increase is therefore not negligible.

Table 6.4 presents the results of specification 6.3, in which each column is the employment in a specific sector of the economy: Agriculture (1), Industry (2), and Services (3). The top panel estimates the model for the full set of countries, while the middle and bottom panels present OECD and non-OECD samples separately. In column (1), the coefficients of interest are positive in the top and middle panel, and negative in the bottom one, but none of them are statistically different from zero. Therefore, no significant association exists between IoT connections and employment in agriculture. Furthermore, the model for agriculture seems to perform rather poorly in terms of R-squared, i.e. the independent variables explain a low share of the variance in the dependent variable. A low R-squared per se is not problematic (Wooldridge, 2015), but its value is particularly low when

Table 6.3: Main results, total employment

	(1) LogEmployment	(2) LogEmployment	(3) LogEmployment	(4) LogEmployment
IoT100	-0.00112**	-0.000233	0.000589***	-0.000810
	(0.000558)	(0.000417)	(0.000181)	(0.000741)
Constant	8.803***	8.647***	3.892***	9.294***
	(0.00640)	(0.650)	(0.716)	(0.728)
Sample	Full	Full	OECD	Non-OECD
Number of countries	107	107	36	71
Controls	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	1,070	1,051	360	691
R-squared	0.581	0.629	0.864	0.618
F-test (p-value)	0	0	0	0

Notes: Cluster Robust standard errors in parentheses. $^{***}p<0.01$,$^{**}p<0.05$,$^{*}p<0.1$

comparing it to the other two specifications with different dependent variables. This may indicate that employment in agriculture, and industry and services follow different trajectories and are affected by very different factors.

While there was no detectable association between the penetration of IoT and employment in the full sample of countries after including control variables (table 6.3), column (2) shows a negative and significant relationship with industry employment at the 5% level. Yet, this result is not supported by a negative and significant β_1 in the OECD sample, and it is loosely negatively correlated in the non-OECD sample, at the 10% level. However, it is important to remember that the introduction of measurement error (through the total number of IoT connections as independent variable) and the results of the Granger-type causality test performed in section 6.1 suggest that this coefficient may be biased. In fact, the estimated β_1 is about four times larger than that found in table 6.3 for OECD countries. This would imply that a 1 connection increase in the number of IoT connections per 100 people is associated with a 0.20% decrease in industry employment, holding everything else constant, which is rather large. Still, the directional result is of note.

Turning to the tertiary sector, no relationship is found with IoT penetration in the full and non-OECD samples of countries. More interestingly, I find a positive and strongly significant coefficient on the IoT penetration measure in the OECD sample: $\beta_1 = 0.00051 (p = 0.005)$. The interpretation of the coefficient is that, within OECD

Table 6.4: Main results, employment by sector

	Log Employment in sector:		
	(1) Agriculture	(2) Industry	(3) Services
Panel A: Full sample			
IoT100	0.00117	-0.00202**	-0.000899
	(0.00119)	(0.000836)	(0.000687)
Constant	6.951***	4.117***	6.276***
	(2.143)	(1.116)	(0.855)
Number of countries	107	107	107
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	1,051	1,051	1,051
R-squared	0.160	0.499	0.719
F-test (p-value)	5.65e-06	0	0
Panel B: OECD Countries			
IoT100	0.000773	8.88e-05	0.000512***
	(0.000829)	(0.000258)	(0.000171)
Constant	5.460***	-1.657	3.771***
	(1.997)	(1.199)	(0.838)
Number of countries	36	36	36
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	360	360	360
R-squared	0.248	0.687	0.897
F-test (p-value)	1.02e-05	0	0
Panel C: Non-OECD Countries			
IoT100	-0.000379	-0.00248*	2.07e-05
	(0.00191)	(0.00135)	(0.00136)
Constant	6.911***	4.859***	6.407***
	(2.592)	(1.268)	(0.935)
Number of countries	71	71	71
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	691	691	691
R-squared	0.170	0.521	0.732
F-test (p-value)	9.17e-05	0	0

Notes: Cluster Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

countries, a 1 unit increase in the number of Internet of Things connections for 100 inhabitants is linked to approximately a 0.05% increase in the employment in the services sector only. This is similar to the result found in table 6.3 with total employment as dependent variable, where $\beta_1 = 0.000589$. In fact, a Chi-square test cannot reject the null hypothesis that the two coefficients are the same ($\chi^2(1) = 0.82, p = 0.36$).

To summarize, there seems to be no significant relationship between the unemployment rate and the number of Internet of Things connections per 100 inhabitants, either in the full sample or the separate samples for OECD and non-OECD countries. In the full sample, some evidence of a negative relationship between IoT penetration and industry employment, but not total employment, was found. Within OECD countries, there is a positive and significant association between the number of IoT connections per 100 inhabitants and the level of employment: a one unit increase in the number of connections is associated with approximately a 0.06% increase in the employment level. This seems to be entirely driven by the growth of employment in the services sector in the same sample. No relationship was found between Internet of Things connections and employment in the agriculture sector, in any sample.

7 Robustness Checks

This section tests the robustness of the results presented in section 6 through estimating different specifications. First, the unemployment level is used in place of the unemployment rate to robustly check whether the absence of a significant relationship holds. Secondly, the second and third specifications, with total employment and employment by sector as dependent variables, are re-estimated after controlling for capital services.

7.1 Unemployment Level

The results shown in section 6 find no significant association between the unemployment rate and the measure of Internet of Things penetration, in either the full sample or the two sub-samples. Bartlett and Partnoy (2020) explore the *"ratio problem"* of linear regression models in which the outcome variable is defined as a ratios, similarly addressed previously outside the economic literature (see for instance Firebaugh and Gibbs (1985) and Kronmal

(1993)). According to Bartlett and Partnoy (2020), a linear regression such as the one estimated in table 6.2, in which the dependent variable is defined as a ratio Y/n, can lead to biased estimates simply because Y, the dependent variable, is scaled by n. The bias can originate in measurement error and omitted variable bias, which arises when the dependent variable is also correlated with $1/n$. Given that in my specification the number of IoT connections is also normalized by the population, which is likely to be highly correlated with the labor force, the estimation of the unemployment rate using a linear regression could lead to bias. Table 7.1 reports the results for the main estimation with the (log) total number of unemployed persons as dependent variable, which is once again taken from the the International Labour Organization's *ILOSTAT* database. Still, none of the coefficients are statistically significant from zero.

Table 7.1: Robustness check, total unemployment

	(1) LogUnemployment	(2) LogUnemployment	(3) LogUnemployment	(4) LogUnemployment
IoT100	-0.00433	-0.00349	0.00208	-0.000662
	(0.00272)	(0.00311)	(0.00152)	(0.00512)
Constant	6.076***	17.08***	36.65***	13.87***
	(0.0297)	(3.261)	(7.779)	(2.994)
Controls	No	Yes	Yes	Yes
Sample	Full	Full	OECD	Non-OECD
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Number of countries	127	112	36	76
Observations	972	832	350	482
R-squared	0.019	0.098	0.245	0.142
F-test (p-value)	0.000683	7.50e-05	0	0.00180

Note: Cluster Robust standard errors in parentheses. ***$p<0.01$,** $p<0.05$,* $p<0.1$

7.2 Controlling for Capital Services

As discussed in section 5.2, the specification estimated earlier are likely to suffer from omitted variable bias. Most notably, I did not control for any measure of capital inputs. While not decisively so, the evidence outlined in section 3 points towards the direction of capital-labor substitution, at least in the short term (see, for instance, Autor et al. (2003)). Capital input would also be correlated with Internet of Things penetration, since capital-intensive countries are more likely to adopt IoT systems at a faster rate. Capital services, defined as the flow of productive services provided by capital assets, is

generally considered a better measure of input than capital stock (Schreyer et al., 2003). Additionally, developed and developing countries tend to invest in different types of capital assets with different marginal products, making cross-country comparisons in capital stocks harder (Inklaar et al., 2019), which is instead taken into account in the capital services measure. This measure includes fixed assets, such as computer hardware, software and databases, telecommunications, transport equipment, other machinery, non-residential construction, research and development and other intellectual property products (OECD, 2019). It also takes into account user costs per unit of capital services provided by each asset type (Schreyer et al., 2003). Unfortunately, consistent and reliable measures of capital services are hard to come across, and few countries produce them in their national statistics. The Penn World Table (Feenstra et al., 2015) provides a volume index of capital services estimated from national account variables which can be transformed into a level variable as described in section C[7]. Still, this is just a proxy for capital services and it is not entirely reliable. This measure is then normalized by population size, and the log of this per capita capital services variable is included in the estimation.

Table 7.2 presents the results of the estimation of the model with total employment as dependent variable. After controlling for capital services, the relationship between IoT connections per 100 inhabitants and log total employment in a country remains positive and significant, within OECD member states, and, additionally, the coefficient in the non-OECD sample is negative and significant, although only at the 10% level. Table C.1 in the appendix reports the results dividing the employment level in the three sectors. The results are generally in line with those presented in section 6. In the OECD sample, the association between the measure of IoT penetration and employment in the services sector is still positive and significant, at the 1% level, and the coefficient is slightly higher. In the full sample, the number of IoT connections is again negatively and significantly, at the 10% level, correlated with industry employment, though the magnitude is smaller: a 1-unit increase in the number of IoT connections per 100 people is associated with an approximate 0.141% decrease in industry employment, everything else equal. A similar negative association is found in the non-OECD sample: a one-unit increase in the number of connections is associated with approximately a 0.326% decrease in employment in the

[7]Note that this is not available for all non-OECD countries, so that number of countries in the full sample decreases from 107 to 94. Appendix C2 lists the countries for which this measure is available.

industry sector. Besides the possible bias coming from the independent variable, discussed in the previous section, it is also worth noticing that the sample is different from the previous estimation.

Table 7.2: Robustness check, total employment controlling for capital services

	(1) LogEmployment	(2) LogEmployment	(3) LogEmployment
IoT100	-1.59e-05	0.000615***	-0.00123*
	(0.000477)	(0.000190)	(0.000675)
Constant	7.719***	3.478***	8.275***
	(0.848)	(0.782)	(0.996)
Sample	Full	OECD	Non-OECD
Number of countries	94	36	58
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	930	360	570
R-squared	0.625	0.867	0.615
F-test (p-value)	0	0	0

Note: Cluster Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

8 Further Analysis

While the results above present an interesting relationship, its causality is undermined by potential endogeneity, as outlined in section 5.2. One way to address endogeneity, be it in the form of omitted variable bias or simultaneity, is to use dynamic panel data models, such as the Arellano-Bond (Arellano and Bond, 1991) and the Arellano–Bover (Arellano and Bover, 1995) or Blundell–Bond (Blundell and Bond, 1998) Generalized Method of Moments (GMM) estimators. These estimators have become widely used in the applied literature in general, as well as in applications on the relationship between technological change and ICTs, and employment (see O'Mahony et al. (2008); Van Roy et al. (2018); Vu (2011)). Dynamic panel data models include past values of the dependent variable to capture its short-run autoregressive behavior. Within this second methodology, I will focus on employment as a dependent variable.

Roodman (2009a) sets a number of conditions under which such estimators are appropriate. They include (i) a *"large N, small T"* panel; (ii) a linear functional relationship; (iii) a

dependent variable that is dynamic and depends on its past realizations; (iv) endogenous independent variables; (v) individual fixed effects; and (vi) heteroskedasticity and autocorrelation within individuals but not across them (Roodman, 2009a). Based on the specification outlined in section 5, I believe my panel ($N = 107, T = 10$) to fulfill all of these assumptions, and that it is reasonable to assume that the employment level in a country is persistent and depends on its past values, especially in the short-term. An additional assumption is that no external instrumental variable is available for the endogenous variable of interest, which is satisfied as discussed in section 5.2.

8.1 Difference and System GMM Estimators

This section provides a brief introduction to the difference and system GMM estimators following Roodman (2009a). Both estimators are designed to fit the following baseline model:

$$y_{i,t} = \alpha y_{i,t-1} + \beta X_{i,t} + \mu_i + \varepsilon_{i,t} \tag{8.1}$$

where the error is composed of a fixed effect term μ_i and an idiosyncratic term $\varepsilon_{i,t}$, and Xi, t is a vector of all regressors. Applying ordinary least squares to this empirical model is problematic, as the lagged term of the dependent variable $y_{i,t-1}$ will be correlated with the time-invariant fixed effect term μ_i of the error, generating "*dynamic panel bias*" (Nickell, 1981). A first way to tackle this bias is to transform the data by taking first differences of equation 8.1:

$$\Delta y_{i,t} = \alpha \Delta y_{i,t-1} + \beta \Delta X_{i,t} + \Delta \varepsilon_{i,t} \tag{8.2}$$

which removes the fixed effects. However, the term $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ is still potentially correlated with $\Delta \varepsilon_{i,t-1} = \varepsilon_{i,t-1} - \varepsilon_{i,t-2}$ through the term $\varepsilon_{i,t-1}$ and hence endogenous, as well as any regressor in X that is not strictly exogenous (Roodman, 2009a). The *differenced*-GMM estimator (Arellano and Bond, 1991) then uses all past values of the untransformed endogenous variables y as instruments for the differenced term $\Delta y_{i,t}$. This applies not only to the lagged dependent variable but also to any endogenous regressors in X. Finally, the coefficients of interest α and β are estimated via a Generalized Method of Moments (GMM), of which OLS and two-stage least squares (2SLS) are special cases (see

Hall (2004) or Wooldridge (2001) for a detailed description of the Generalized Method of Moments).

A second approach to panel data bias is that of Arellano and Bover (1995), which removes the fixed effects by differencing the instruments, instead of transforming the data. Therefore, while Arellano and Bond (1991) instruments differences with levels, Arellano and Bover (1995) instruments levels with differences. Blundell and Bond (1998) exploits these additional moment conditions by simultaneously estimating the instrumented levels (eq. 8.1) and the differenced equation (eq. 8.2) in a system. Blundell and Bond (1998) show, through Monte Carlo simulations, that this *system*-GMM estimator is less biased than the difference-GMM estimator, in particular in two cases: when the sample is small, and when the dependent variable is highly persistent[8]. If the endogenous variable is highly persistent, its past levels convey little information about its future changes and will therefore be weak instruments for the differenced equation. By estimating the levels equation, it is also possible to include time-invariant variables, such as year dummies, in a system-GMM estimation.

While GMM and dynamic panel models are useful tools in the presence of endogeneity, they are also complex and their use involves many choices, resulting in a high number of researcher degrees of freedom. Roodman (2009a) warns that the application of such estimators may result in a 'black box'[9] situation and can easily generate invalid estimates. Additionally, the cross sectional dimension of the panel may not be large enough, and the typical concerns of an instrumental variable approach, in terms of relevance and validity, still apply.

[8]Both apply in this case. Despite being large enough for a dynamic panel model estimation, the cross-sectional and time series dimensions of the panel are both rather limited. Tables 8.1, D.1 and D.2 all show a high autoregressive coefficient α, which is always higher than 0.90.

[9]The Merriam-Webster dictionary defines a black box as "a usually complicated electronic device whose internal mechanism is usually hidden from or mysterious to the user" (Merriam-Webster, 2021).

8.2 Estimation and Results

As an attempt to address endogeneity, I will apply a system-GMM estimator to the following equations:

$$\begin{aligned} Log(Employment_{it}) = \alpha Log(Employment_{it-1}) + \beta_0 + \beta_1 IoT_{it} \\ + \gamma X_{it} + a_i + a_t + \varepsilon_{it} \end{aligned} \tag{8.3}$$

$$\begin{aligned} Log(Employment_{it,j}) = \alpha Log(Employment_{it-1,j}) + \beta_0 + \beta_1 IoT_{it} \\ + \gamma X_{it} + a_i + a_t + \varepsilon_{it} \end{aligned} \tag{8.4}$$

where both the right hand side and the left hand side are defined as before, and a 1-year lag of the dependent variable is included. Post-estimation tests are conducted to check the validity of the model. In particular, Arellano-Bond autocorrelation tests for differenced residuals $\Delta\varepsilon_{i,t}$ are run. First-order autocorrelation, between $\Delta\varepsilon_{i,t}$ and $\Delta\varepsilon_{i,t-1}$, is to be expected because of the shared term $\varepsilon_{i,t-1}$, while second-order autocorrelation should not be detected. In addition, since endogenous variables are instrumented with past realizations, the Hansen test of overidentifying restrictions should be run to test for validity of the instruments. In all estimations, Windmeijer finite sample correction is applied (Windmeijer, 2005), and Windmeijer cluster-robust standard errors are reported, which reduce the downward bias of traditional two-step GMM computed standard errors (Roodman, 2009a).

Applying the estimation above to the sub-sample analysis carried out in section 6 poses an additional concern because of the smaller samples (N). In particular, the number of instruments has to be limited in order to avoid overfitting and instrument proliferation (Roodman, 2009a). In this section, I will focus on baseline specifications 8.3 and 8.4 within OECD countries, since it was the one for which the strongest evidence of a significant association was found in the two-way fixed effect estimation. Estimations for the full set of countries and non-OECD countries are available in appendix D.

Table 8.1 shows the results of the system GMM estimation where the endogenous variables (the autoregressive term and the IoT measure) are instrumented with lags two and longer

in the level equation. As a general rule of thumb, Roodman (2009a) suggests that the number of instruments should not outnumber the individuals, which is the case here. Post estimation checks of Arellano-Bond second-order correlation are satisfied: the test cannot reject the null hypothesis of no serial correlation, and therefore second lags of the endogenous variables qualify as valid instruments. The null of overidentifying restrictions is also not rejected by the Hansen test in any of the four specifications. However, the p-value Hansen J statistic in column (1) is high ($p = 0.914$) which suggests that the number of the instruments may still be high, since the p-value goes to 1 as many instruments are included (Roodman, 2009b). If this is the case, the GMM coefficients will be biased towards OLS estimated ones that suffer from typical endogeneity bias (Roodman, 2009a). This, together with the fact that the Arellano-Bond test fails to detect first-order serial correlation in the differenced residuals, suggests that the model may not be correctly specified.

Table 8.1: System GMM estimation, OECD sample

	(1) LogEmployment	(2) LogAgricultureEmp	(3) LogIndustryEmp	(4) LogServicesEmp
$\text{LogEmployment}_{t-1}$	0.947***			
	(0.0223)			
$\text{LogAgricultureEmp}_{t-1}$		0.994***		
		(0.0328)		
$\text{LogIndustryEmp}_{t-1}$			0.909***	
			(0.0616)	
$\text{LogServicesEmp}_{t-1}$				0.942***
				(0.0310)
IoT100	0.000532**	5.40e-05	0.000584**	0.000511*
	(0.000257)	(0.000336)	(0.000247)	(0.000310)
Constant	0.726*	0.212	1.458*	0.478
	(0.358)	(0.887)	(0.737)	(0.305)
Observations	324	324	324	324
Number of countries	36	36	36	36
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AR(1)	0.131	0.000207	0.0392	0.0328
AR(2)	0.421	0.168	0.419	0.335
Hansen	0.914	0.553	0.702	0.558
Number of Instruments	35	35	35	35

Notes: Two-step system GMM estimation where the lag of the dependent variable and the endogenous regressor are instrumented with lags 2 and longer for the transformed equation and lag 1 for the levels equation, and instruments are collapsed. AR(1), AR(2) and Hansen report p-values for the respective tests. Finite sample correction applied to all estimations, Windmeijer-corrected cluster–robust errors in parentheses. Estimation run with the command 'xtabond2' in Stata. *** p<0.01, ** p<0.05, * p<0.1.

The results show that the coefficients for the IoT penetration variable are close to those

found in the two-way fixed effect estimation (tables 6.3 and 6.4). The coefficient of interest is again significant in the estimation of (log) total employment, at the 5% significance level, and in the estimation of (log) employment in services, though only at the 10% level. In this system-GMM estimation, additionally, the coefficient on IoT connections in column (3), with (log) industry employment as a dependent variable, is also significant at the 5% level, and similar in magnitude to the other two. However, given the misspecification reported above, any conclusion on causal inference is out of reach. The results for the full sample and the non-OECD sample are reported in table D.1 and D.2. In both cases, the results support the evidence of no correlation between the measure of IoT penetration and either total employment, employment in agriculture of services found in section 6. Likewise, the negative correlation between industry employment and the measure of IoT usage in the full sample of countries did not remain robust to this different specification.

9 Discussion

In this section I discuss the results presented in the previous sections, the limitations of the analysis and opportunities for further research.

To summarize the results, I find that an increased penetration of Internet of Things, defined as the number of cellular IoT connections per 100 inhabitants, is positively and significantly associated with employment within OECD member countries: everything else equal, a one connection increase is approximately associated with a 0.058% increase in total employment, driven by a positive and significant relationship of similar magnitude with employment in the services sector. This finding remains robust to the inclusion of capital services as a control, though the evidence from the dynamic panel data estimation was not conclusive. This effect is confined to higher income OECD countries, as no analogous evidence was found in either the full sample or the non-OECD sample. In the full sample, a negative correlation was found between the measure of IoT usage and employment in the industry sector, and some evidence that this may be driven by non-OECD countries, though no correspondence of this was found in the system-GMM estimation. The magnitude of the effect, however, seems to be unlikely high due to bias in the specification. No significant association was found between the number of cellular Internet of Things connections and the other dependent variable, the unemployment rate.

I find the results on employment to be reasonable, both in scope and size, given the limited years considered and the fact that OECD countries started out with a larger usage of the Internet of Things and saw a more substantial growth in the number of connections per capita.

It is interesting to notice that I find a positive and significant, at the 1% level, correlation between IoT and total employment and employment in services, but not unemployment. Although it is not possible to provide any insight on the mechanisms through this analysis, one possible explanation is that, as the usage of IoT technologies within a country increases, new jobs are created and more people enter the labor force, in particular in the services sector. To relate this to the theoretical framework presented in the literature review, this could either be the result of increased productivity and increased demand for labor in non-automated tasks, or the result of the creation of new tasks in which human labor has a comparative advantage that offsets the displacement of workers in automated tasks. Both of them seem to be viable channels. Edquist et al. (2021) already found a positive association between IoT adoption and productivity, which, coupled with the results presented above, supports the existence of a *productivity* effect. Yet it is also easy to see how, in the early years of adoption, the Internet of Things could create new jobs and demand for workers in the services sector, such as engineers and ICT specialist to work on IoT deployment. This, instead, points towards the presence of a *reinstatement* effect, as defined by Acemoglu and Restrepo (2019). The negative relationship with industry employment is perhaps the intuitive result when looking at IoT as a tool for automation: as IoT usage increases, capital substitutes labor in automated tasks within manufacturing. If both apply, this may suggest that there are winners and losers of IoT implementation.

The results are also in line with previous literature within automation and Information and communication technologies. Kolko (2012) find a positive, although limited, causal effect of broadband availability on local employment, while Czernich (2014) finds broadband to be neutral to unemployment. The differential effect between OECD and non-OECD member countries is also a common theme in the literature (see Roller and Waverman (2001), Edquist et al. (2018), Thompson Jr and Garbacz (2007)). Similarly, Autor et al. (2003) find reduced employment in routine tasks (both manual and cognitive) and increased employment in nonroutine cognitive tasks as a result of computerization. Finally, the

results point in a similar direction of increased employment among adopters as in the preliminary firm-level evidence presented by Kariel (2021).

Overall, inferring causality in this context has proved a hard task, and applying a system GMM estimator has proved inconclusive. It is worth noting that even if the variable of interest, Internet of Things connections per 100 inhabitants, had been in fact exogenous, a fixed effect model would identify the average effect on the treated (Collischon and Eberl, 2020), those who selected into, in this case OECD countries. It would therefore still not be possible to generalize the effect to the wider set of countries. Moreover, a fixed effect OLS estimator will not be consistent in the presence of heterogeneity of treatment effect across countries or over the years (Gibbons et al., 2019). A second limitation of this thesis is the data used. While the data is of very high quality, it only includes IoT connections that use cellular technology, and is only available at the country-level. There is, to my knowledge and research, no available data on IoT connections based on other technologies, such as Wi-Fi. While there is no current estimate of what market share each technology has, the scope of this paper is nevertheless limited.

Further research within the economic impact of the Internet of Things is needed and encouraged. In particular, much of the potential research on IoT relies on the availability of new or more comprehensive data. The availability of data that is aggregated at a smaller level, such as within a country or even firm-level data, would make it possible to more precisely estimate the association that I have found and to potentially describe the mechanisms that drive it. In particular, industry-level data would allow to more precisely estimate within-sector effects. Obtaining within-country data for multiple countries would allow for testing whether the effects are heterogeneous across countries. The results I have found are estimated for a short panel; having a longer panel would prove useful in identifying whether there are decreasing returns to its usage. Finally, finding a suitable instrumental variable could provide insights on the causality of the relationship.

10 Conclusion

In this thesis, I first described a new technological paradigm known as the Internet of Things, its trends and the wide range of applications that go beyond popular consumer

devices. The public discourse has thus far focused on its privacy and security implications, and the evidence on its economic impact is still limited. Even so, early evidence suggests the presence of a positive relationship between IoT usage and productivity and growth across countries (Edquist et al. (2021), Espinoza et al. (2020)). Hence, it may be possible for this positive impact on productivity to have spilled over the demand for labor inputs.

Throughout this paper, I first construct a panel of 107 developed and developing countries across ten years, from 2010 to 2019, with country-level data on the number of mobile IoT connections and economic variables. I define IoT penetration as the number of mobile IoT connections over 100 inhabitants in a country, and study its relationship with different labor outcomes. Applying a two-way fixed effects estimation, I find a positive and significant relationship between IoT usage and the employment level in a country within OECD countries in the years considered, after controlling for a number of economic and demographic covariates. Under this specification, I find that an increase of one connection per 100 inhabitants is associated to approximately a 0.059% increase in total employment in a country for OECD member states, everything else equal. When breaking down total employment into the three different sectors of the economy, the previous result seems to be driven by a positive relationship between my measure of IoT penetration and employment in the services sector in the same sample: a one unit increase in connections per 100 inhabitants is associated with approximately a 0.051% increase in employment in the services sector, ceteris paribus. No significant relationship was found with the unemployment rate, either in the full sample of countries or the two restricted sub-samples, while a negative and less robust relationship with industry employment in the full and non-OECD sample was found.

The results are in line with previous empirical research within information and communication technologies, which find a positive, or at least non-negative, impact of ICTs on employment, and differential effects between OECD and non-OECD countries. On the other hand, the negative result found within the industry sector is consistent with the literature on automation, which reports varying degrees of capital-labor substitution. Nevertheless, inferring causality from the estimation is challenging, given potential omitted variable and simultaneity bias that affects my model. In an attempt to tackle causality, a dynamic panel data model with a system-GMM estimator was applied. While the

magnitude was similar, a causal interpretation remains out of reach. Nonetheless, the correlations presented are still somewhat informative of evidence from early adoption of the technology.

This thesis is, to the best of my knowledge, the first empirical study to try and estimate a relationship between the Internet of Things usage and labor outcomes in the early years after its introduction. No policy recommendations can be set on the results, since no causal mechanism has been identified. It is yet perhaps of interest to notice that despite the recurring worry that new technologies and automation would make workers redundant, limited supporting evidence was found in the case of IoT, at least in the short-run, and, within higher income countries, only a positive relationship was established. The channels through which this association takes place, as well as any country-heterogeneous effects and micro-level evidence, are left to further research.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., and Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics*, 34(S1):S141–S198.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30.

Acemoglu, D. and Restrepo, P. (2020). Unpacking skill bias: Automation and new tasks. In *AEA Papers and Proceedings*, volume 110, pages 356–61.

Ahlgren, B., Hidell, M., and Ngai, E. C.-H. (2016). Internet of Things for smart cities: Interoperability and open data. *IEEE Internet Computing*, 20(6):52–56.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1):29–51.

Arntz, M., Gregory, T., and Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. OECD Social, Employment and Migration Working Papers no. 189. OECD Publishing.

Atasoy, H. (2013). The effects of broadband internet expansion on labor market outcomes. *ILR Review*, 66(2):315–345.

Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The China shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8:205–240.

Autor, D. H., Dorn, D., Hanson, G. H., and Song, J. (2014). Trade adjustment: Worker-level evidence. *The Quarterly Journal of Economics*, 129(4):1799–1860.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Balsmeier, B. and Woerter, M. (2019). Is this time different? how digitalization influences job creation and destruction. *Research Policy*, 48(8):103765.

Bartlett, R. P. and Partnoy, F. (2020). The ratio problem. *Available at https://ssrn.com/abstract=3605606*.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275.

Bertschek, I., Briglauer, W., Hüschelrath, K., Kauf, B., and Niebel, T. (2015). The economic impacts of broadband internet: A survey. *Review of Network Economics*, 14(4):201–227.

Biagi, F. and Falk, M. (2017). The impact of ICT and e-commerce on employment in Europe. *Journal of Policy Modeling*, 39(1):1–18.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1):115–143.

Bouis, R., Causa, O., Demmou, L., Duval, R., and Zdzienicka, A. (2012). The short-term effects of structural reforms: an empirical analysis. OECD Economics Department Working Paper no. 949. OECD Publishing.

Bresnahan, T. F. and Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of Econometrics*, 65(1):83–108.

Brynjolfsson, E. and Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of Economics and Statistics*, 85(4):793–808.

Bulligan, G., Guglielminetti, E., and Viviano, E. (2019). Adjustments along the intensive margin and wages: Evidence from the euro area and the US.

Chettri, L. and Bera, R. (2020). A Comprehensive Survey on Internet of Things (IoT) Toward 5G Wireless Systems. *IEEE Internet of Things Journal*, 7(1):16–32.

Chinn, M. D. and Fairlie, R. W. (2007). The determinants of the global digital divide: a cross-country analysis of computer and internet penetration. *Oxford Economic Papers*, 59(1):16–44.

Collischon, M. and Eberl, A. (2020). Let's talk about fixed effects: Let's talk about all the good things and the bad things. *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*, 72(2):289–299.

Crandall, R. W., Lehr, W., and Litan, R. E. (2007). The effects of broadband deployment on output and employment: A cross-sectional analysis of US data. *Issues in Economic Policy*. The Brookings Institution.

Czernich, N. (2014). Does broadband internet reduce the unemployment rate? Evidence for Germany. *Information Economics and Policy*, 29:32–45.

Czernich, N., Falck, O., Kretschmer, T., and Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal*, 121(552):505–532.

Edquist, H., Goodridge, P., and Haskel, J. (2021). The Internet of Things and economic growth in a panel of countries. *Economics of Innovation and New Technology*, 30(3):262–283.

Edquist, H., Goodridge, P., Haskel, J., Li, X., and Lindquist, E. (2018). How important are mobile broadband networks for the global economic development? *Information Economics and Policy*, 45:16–29.

Espinoza, H., Kling, G., McGroarty, F., O'Mahony, M., and Ziouvelou, X. (2020). Estimating the impact of the Internet of Things on productivity in Europe. *Heliyon*, 6(5):e03935.

European Commission (2016). Advancing the Internet of Things in Europe. Commission Staff Working Document. Available at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52016SC0110.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the Penn World Table. *American economic review*, 105(10):3150–82.

Firebaugh, G. and Gibbs, J. P. (1985). User's guide to ratio variables. *American Sociological Review*, pages 713–722.

Fleisch, E. (2010). What is the Internet of Things? an economic perspective. *Economics, Management, and Financial Markets*, 5(2):125–157.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Gibbons, C. E., Serrato, J. C. S., and Urbancic, M. B. (2019). Broken or fixed effects? *Journal of Econometric Methods*, 8(1).

Goodridge, P., Haskel, J., and Edquist, H. O. (2019). Productivity, network effects and telecommunications capital: Evidence from the US and Europe. CEPR Discussion Paper No. DP13910.

GSMA (2021). GSMA Intelligence Database. Available at https://www.gsmaintelligence.com/.

Hall, A. R. (2004). *Generalized method of moments*. Oxford University Press.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, pages 1251–1271.

Hogan, O., Holdgate, L., and Jayasuriya, R. (2016). The Value of Big Data and the Internet of Things to the UK Economy. Report for SAS. Centre for Economics and Business Research.

Höller, J., Tsiatsis, V., Mulligan, C., Karnouskos, S., Avesand, S., and Boyle, D. (2014). *From Machine-to-Machine to the Internet of Things: Introduction to a New Age of Intelligence*. Elsevier Science.

Inklaar, R., Woltjer, P., Albarrán, D. G., and Gallardo, D. (2019). The composition of capital and cross-country productivity comparisons. *International Productivity Monitor*, 36:34–52.

International Labour Organization (2021). Ilostat database: ILO modelled estimates (ILOEST). Available at https://ilostat.ilo.org/data/.

International Telecommunication Union (2012). Overview of the Internet of Things. Recommendation ITU-T Y.2060.

International Telecommunication Union (2021). World telecommunication/ICT indicators database.

Jayakar, K. and Park, E.-A. (2013). Broadband availability and employment: An analysis of county-level data from the national broadband map. *Journal of Information Policy*, 3:181–200.

Jorgenson, D. W., Ho, M. S., and Stiroh, K. J. (2008). A retrospective look at the US productivity growth resurgence. *Journal of Economic Perspectives*, 22(1):3–24.

Karabarbounis, L. and Neiman, B. (2014). The global decline of the labor share. *The Quarterly Journal of Economics*, 129(1):61–103.

Kariel, J. (2021). Firms that automate: Evidence and theory. Available at https://www.joelkariel.com/publication/example2/.

Kechiche, S. (2020). Enterprises speak: IoT gets real. Available at https://www.gsmaintelligence.com/.

Kechiche, S., Zhong, Y., and Giles, M. (2020). IoT revenue: state of the market 2020. Available at https://www.gsmaintelligence.com/.

Keynes, J. M. (1933). Economic possibilities for our grandchildren. In *Essays in persuasion*, pages 321–332. Springer.

Kolko, J. (2012). Broadband and local growth. *Journal of Urban Economics*, 71(1):100–113.

Kronmal, R. A. (1993). Spurious correlation and the fallacy of the ratio standard revisited. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 156(3):379–392.

Kshetri, N. (2017). The evolution of the Internet of Things industry and market in China: An interplay of institutions, demands and supply. *Telecommunications Policy*, 41(1):49–67.

Lam, P.-L. and Shiu, A. (2010). Economic growth, telecommunications development and productivity growth of the telecommunications sector: Evidence around the world. *Telecommunications Policy*, 34(4):185–199.

Li, Y., Guo, Y., and Chen, S. (2018). A survey on the development and challenges of the Internet of Things (IoT) in China. In *2018 International Symposium in Sensing and Instrumentation in IoT Era (ISSI)*, pages 1–5. IEEE.

Lindman, J. and Saarikko, T. (2019). Towards an Internet of Things society: Perspectives from government agencies in Sweden. In *Proceedings of the 52nd Hawaii international conference on system sciences*.

Manyika, J., Chui, M., Bisson, P., Woetzel, J., Dobbs, R., Bughin, J., and Aharon, D. (2015). The Internet of Things: Mapping the value beyond the hype. McKinsey Global Institute.

Merriam-Webster (2021). Black box. In *Merriam-Webster.com dictionary*.

Moretti, E. (2011). Local labor markets. In *Handbook of Labor Economics*, volume 4, pages 1237–1313. Elsevier.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, pages 1417–1426.

OECD (2009). Measuring Capital - OECD Manual 2009: Second Edition. OECD Publishing.

OECD (2011). Guide to measuring the information society. OECD Publishing.

OECD (2016). The Internet of Things: Seizing the benefits and addressing the challenges. OECD Digital Economy Papers no. 252. OECD Publishing.

OECD (2019). OECD compendium of productivity indicators 2019. OECD Publishing.

OECD (2019). Recommendation of the council on artificial intelligence. OECD legal instruments. OECD Publishing.

OECD (2021). Broadband database (edition 2019). Available at https://www.oecd-ilibrary.org/content/data/cdacdf78-en.

Ohanian, L. E. and Raffo, A. (2012). Aggregate hours worked in OECD countries: New measurement and implications for business cycles. *Journal of Monetary Economics*, 59(1):40–56.

Oliner, S. D. and Sichel, D. E. (2000). The resurgence of growth in the late 1990s: is information technology the story? *Journal of Economic Perspectives*, 14(4):3–22.

O'Mahony, M., Robinson, C., and Vecchi, M. (2008). The impact of ICT on the demand for skilled labour: A cross-country comparison. *Labour Economics*, 15(6):1435–1450.

O'Mahony, M. and Vecchi, M. (2005). Quantifying the impact of ICT capital on output growth: a heterogeneous dynamic panel approach. *Economica*, 72(288):615–633.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861-1957. *Economica*, 25(100):283–299.

Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica*, 77(5):1339–1369.

Prieger, J. E. (2013). The broadband digital divide and the economic benefits of mobile broadband for rural areas. *Telecommunications Policy*, 37(6-7):483–502.

Rogerson, R. (2006). Understanding differences in hours worked. *Review of Economic Dynamics*, 9(3):365–409.

Roller, L.-H. and Waverman, L. (2001). Telecommunications infrastructure and economic development: A simultaneous approach. *American Economic Review*, 91(4):909–923.

Romer, C. (1986). Spurious volatility in historical unemployment data. *Journal of Political Economy*, 94(1):1–37.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, 9(1):86–136.

Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1):135–158.

Ryberg, T. (2019). The Global M2M/IoT Communications Market: IoT Research Series 2019. Bergh Insights.

Sale, K. (1995). *Rebels against the future: lessons for the computer age*. Quartet Books Limited.

SAS (2021). IoT data with artificial intelligence reduces downtime, helps truckers keep on trucking. Available at https://www.sas.com/en_us/customers/volvo-trucks-mack-trucks.html.

Say, J. B. (1836). *A treatise on political economy: or the production, distribution, and consumption of wealth.* Grigg & Elliot.

Schreyer, P., Bignon, P.-E., and Dupont, J. (2003). OECD capital services estimates: Methodology and a first set of results. OECD Statistics Working Papers no. 2003/06. OECD Publishing.

Sinha, R. S., Wei, Y., and Hwang, S.-H. (2017). A survey on LPWA technology: LoRa and NB-IoT. *ICT Express*, 3(1):14–21.

Sivakumaran, M. (2019). The contribution of IoT to economic growth. Available at https://www.gsmaintelligence.com/.

Stanley, T. D., Doucouliagos, H., and Steel, P. (2018). Does ICT generate economic growth? a meta-regression analysis. *Journal of Economic Surveys*, 32(3):705–726.

The Conference Board (2021). Total economy database™, August 2021. Available at https://conference-board.org/data/economydatabase/total-economy-database-productivity.

Thompson Jr, H. G. and Garbacz, C. (2007). Mobile, fixed line and internet service effects on global productive efficiency. *Information Economics and Policy*, 19(2):189–214.

Van Ark, B., O'Mahoney, M., and Timmer, M. P. (2008). The productivity gap between Europe and the United States: trends and causes. *Journal of Economic Perspectives*, 22(1):25–44.

Van Roy, V., Vértesy, D., and Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research Policy*, 47(9):1762–1776.

Venturini, F. (2009). The long-run impact of ICT. *Empirical Economics*, 37(3):497–515.

Venturini, F., Rincon-Aznar, A., and Vecchi, M. (2013). ICT as a general purpose technology: spillovers, absorptive capacity and productivity performance. National Institute of Economic and Social Research (NIESR) Discussion Papers 416.

Vu, K., Hanafizadeh, P., and Bohlin, E. (2020). ICT as a driver of economic growth: A survey of the literature and directions for future research. *Telecommunications Policy*, 44(2):101922.

Vu, K. M. (2011). ICT as a source of economic growth in the information age: Empirical evidence from the 1996–2005 period. *Telecommunications Policy*, 35(4):357–372.

Warschauer, M. (2003). Demystifying the digital divide. *Scientific American*, 289(2):42–47.

Waverman, L., Meschi, M., and Fuss, M. (2005). The impact of telecoms on economic growth in developing countries. *The Vodafone Policy Paper Series*, 2(03):10–24.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, 126(1):25–51.

Wooldridge, J. M. (2001). Applications of generalized method of moments estimation. *Journal of Economic Perspectives*, 15(4):87–100.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Cengage learning.

World Bank (2021). World Development Indicators Database. Available at https://databank.worldbank.org/source/world-development-indicators.

Appendix

A Data

A1 List of countries

OECD Countries:

Australia; Austria; Belgium; Canada; Chile; Czechia; Denmark; Estonia; Finland; France; Germany; Greece; Hungary; Iceland; Ireland; Israel; Italy; Japan; Latvia; Lithuania; Luxembourg; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Slovakia; Slovenia; South Korea; Spain; Sweden; Switzerland; Turkey; United Kingdom; United States of America.

Non-OECD countries and territories:

Albania; Algeria; Angola; Argentina; Armenia; Bahrain; Bangladesh; Bolivia; Botswana; Brazil; Bulgaria; Burkina Faso; Cambodia; Cameroon; China; Colombia; Costa Rica; Cote d'Ivoire; Croatia; Cyprus; Democratic Republic of the Congo; Dominican Republic; Ecuador; Egypt; Ethiopia; Ghana; Hong Kong; India; Indonesia; Iran; Jamaica; Jordan; Kazakhstan; Kenya; Kuwait; Kyrgyzstan; Madagascar; Malaysia; Mali; Malta; Mauritius; Moldova; Morocco; Mozambique; Namibia; Niger; Nigeria; Pakistan; Paraguay; Peru; Philippines; Qatar; Romania; Russian Federation; Rwanda; Saudi Arabia; Senegal; Singapore; South Africa; Sri Lanka; Sudan; Tanzania; Thailand; Tunisia; Uganda; Ukraine; United Arab Emirates; Uruguay; Vietnam; Zambia; Zimbabwe.

A2 Summary tables

Table A.1: Descriptive statistics by sample (2010-2019)

	Mean	St. Dev.	Min	Max	N
OECD Sample					
Unemployment rate (in %)	7.83	4.50	2.01	27.47	360
Unemployment (in thousands)	1,190	1,943	5	15,100	360
Employment (in thousands)	16,283	27,318	163	159,073	360
Employment in Agriculture (in thousands)	768	1,425	3	6,882	360
Employment in Industry (in thousands)	3,745	5,857	30	31,671	360
Employment in Services (in thousands)	11,770	20,912	123	125,254	360
Working-age population (in thousands)	23,355	38,456	216	215,318	360
IoT connections*	12.85	15.65	0.56	146.37	360
Per Capita GDP	45,652	17,390	19,329	120,408	360
Population Density	138.69	136.34	2.91	525.50	360
Inflation rate (in %)	1.94	2.14	-2.96	16.49	360
Trade (% of GDP)	103.48	63.60	26.29	408.36	360
Human Capital	3.32	0.35	2.21	3.89	360
Total mobile connections*	125.14	22.16	72.83	181.37	360
Fixed Broadband subscriptions*	30.07	8.22	9.21	46.65	360
Non-OECD Sample					
Unemployment rate (in %)	6.81	5.24	0.11	28.47	710
Unemployment (in thousands)	1,827	5,340	2	37,112	710
Employment (in thousands)	33,100	105,267	164	762,101	710
Employment in Agriculture (in thousands)	11,519	37,452	1	278,797	710
Employment in Industry (in thousands)	7,797	29,214	38	230,629	710
Employment in Services (in thousands)	13,785	40,879	120	355,838	710
Working-age population (in thousands)	50,905	155,810	286	1,024,188	710
IoT connections*	2.65	4.91	0	85.51	710
Per Capita GDP	17,476	21,286	813	115,064	710
Population Density	371.25	1,231.98	2.60	8,219.10	710
Inflation rate (in %)	6.74	15.44	-25.96	350.00	710
Trade (% of GDP)	85.06	65.67	16.14	442.62	708
Human Capital	2.44	0.61	1.17	4.35	710
Total mobile connections*	108.76	39.71	9.68	202.10	710
Fixed Broadband subscriptions*	7.68	9.04	0	45.93	693

*Connections and subscriptions expressed per 100 inhabitants.

B Main Results

Table B.1: Granger causality-type test by sample

			Log Employment in sector:		
	(1) UnemploymentR	(2) LogEmployment	(3) Agriculture	(4) Industry	(5) Services
Panel A: OECD sample					
IoT100_{t-2}	0.203**	-0.000330	-0.000161	-0.00286	-8.94e-05
	(0.0763)	(0.000717)	(0.00423)	(0.00170)	(0.000745)
IoT100_{t-1}	-0.0786**	0.000637	0.000606	0.000865	0.000517
	(0.0328)	(0.000537)	(0.00326)	(0.00171)	(0.000539)
IoT100_{t}	-0.00798	-5.86e-05	-0.00236	0.000535	0.000140
	(0.0236)	(0.000345)	(0.00246)	(0.000621)	(0.000544)
IoT100_{t+1}	-0.0254	0.000149	0.00275***	0.000338	-0.000117
	(0.0203)	(0.000240)	(0.00101)	(0.000360)	(0.000234)
Constant	304.9***	3.671***	7.738**	-2.400	3.433***
	(72.11)	(0.959)	(3.221)	(1.422)	(1.033)
Sample	OECD	OECD	OECD	OECD	OECD
Number of countries	36	36	36	36	36
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252
R-squared	0.729	0.870	0.228	0.670	0.890
F-test (p-value)	0	0	5.98e-06	4.21e-10	0
Panel A: Non-OECD sample					
IoT100_{t-2}	-0.751	-1.12e-05	0.0731**	-0.0110	-0.0115
	(0.454)	(0.0125)	(0.0322)	(0.0207)	(0.00935)
IoT100_{t-1}	0.675	-0.00217	-0.103*	0.00433	-0.00327
	(0.580)	(0.0217)	(0.0571)	(0.0324)	(0.0178)
IoT100_{t}	-0.377*	0.00154	0.0291	0.00384	-0.00107
	(0.226)	(0.00831)	(0.0216)	(0.0123)	(0.00785)
IoT100_{t+1}	0.162*	-0.000941	0.000572	-0.00415	0.00323
	(0.0933)	(0.00156)	(0.00427)	(0.00254)	(0.00228)
Constant	89.62***	8.833***	5.965	4.273***	6.802***
	(19.92)	(1.010)	(3.646)	(1.358)	(1.002)
Sample	Non-OECD	Non-OECD	Non-OECD	Non-OECD	Non-OECD
Number of countries	71	71	71	71	71
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	489	489	489	489	489
R-squared	0.222	0.545	0.136	0.464	0.706
F-test (p-value)	0.000122	0	8.44e-10	0	0

Note: Cluster Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

C Robustness

C1 Capital services measure estimation

In order to construct a measure of capital services that is comparable across countries, I use two variables available in the Penn World Table version 10.0 (Feenstra et al., 2015), which are computed based on national account estimates. The first is an index of *Capital services at constant 2017 national prices*, which is equal to 1 in 2017 for all countries and other years are relative to 2017, and therefore proxies for growth in capital services. The second variable used is *Capital stock at constant 2017 national prices in 2017US$*. The capital service measure is then constructed by taking, for each country, the benchmark value for capital stock in 2017 and multiplying it by the capital services index, i.e. the share of capital services in each year relative to 2017. A similar imputation is used, among others, by Edquist et al. (2018). By construction, this measure of capital services is equal to capital stock in 2017 for each country, and it implies that the share of capital services relative to capital stock is not changing over time. This is appropriate, since capital services are assumed to be in fixed proportion to capital stock (OECD, 2009). Nevertheless, it is still a proxy.

C2 Countries for which the capital services measure is available

Angola; Argentina; Armenia; Australia; Austria; Bahrain; Belgium; Bolivia; Botswana; Brazil; Bulgaria; Burkina Faso; Cameroon; Canada; Chile; China; Colombia; Costa Rica; Cote d'Ivoire; Croatia; Cyprus; Czechia; Denmark; Dominican Republic; Ecuador; Egypt; Estonia; Finland; France; Germany; Greece; Hong Kong; SAR China; Hungary; Iceland; India; Indonesia; Iran; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Korea; South; Kuwait; Kyrgyzstan; Latvia; Lithuania; Luxembourg; Malaysia; Malta; Mauritius; Mexico; Moldova; Morocco; Mozambique; Namibia; Netherlands; New Zealand; Niger; Nigeria; Norway; Paraguay; Peru; Philippines; Poland; Portugal; Qatar; Romania; Russian Federation; Rwanda; Saudi Arabia; Senegal; Singapore; Slovakia; Slovenia; South Africa; Spain; Sri Lanka; Sudan; Sweden; Switzerland; Tanzania; Thailand; Tunisia; Turkey; Ukraine; United Kingdom; United States of America; Uruguay; Zambia; Zimbabwe.

C3 Empirical estimation

Table C.1: Robustness check, employment by sector controlling for capital services

	Log Employment in sector:		
	Agriculture	Industry	Services
Panel A: Full sample			
IoT100	0.00144	-0.00141*	-0.000460
	(0.00128)	(0.000755)	(0.000497)
Constant	6.602***	2.840**	4.800***
	(2.086)	(1.236)	(1.132)
Number of countries	94	94	94
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	930	930	930
R-squared	0.163	0.502	0.747
F-test (p-value)	0.000187	0	0
Panel B: OECD Countries			
IoT100	0.000911	0.000104	0.000550***
	(0.000809)	(0.000265)	(0.000184)
Constant	3.230	-1.907	3.161***
	(2.735)	(1.421)	(0.884)
Number of countries	36	36	36
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
R-squared	0.270	0.687	0.901
F-test (p-value)	7.02e-06	0	0
Panel C: Non-OECD Countries			
IoT100	-3.48e-05	-0.00316***	-0.000805
	(0.00227)	(0.00117)	(0.00124)
Constant	6.507**	3.451**	4.900***
	(2.811)	(1.484)	(1.437)
Number of countries	58	58	58
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Observations	570	570	570
R-squared	0.175	0.528	0.748
F-test (p-value)	0.000936	0	0

Note: Cluster Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

D Further Analysis

Table D.1: System GMM estimation, full sample

	(1) LogEmployment	(2) LogAgricultureEmp	(3) LogIndustryEmp	(4) LogServicesEmp
$\text{LogEmployment}_{t-1}$	0.987***			
	(0.00411)			
$\text{LogAgricultureEmp}_{t-1}$		0.980***		
		(0.00881)		
$\text{LogIndustryEmp}_{t-1}$			0.985***	
			(0.00574)	
$\text{LogServicesEmp}_{t-1}$				0.987***
				(0.00425)
IoT100	0.000108	-8.66e-05	1.72e-05	9.91e-05
	(9.57e-05)	(0.000276)	(0.000144)	(0.000119)
Constant	0.128***	0.388***	0.148***	0.176***
	(0.0430)	(0.143)	(0.0492)	(0.0420)
Observations	947	947	947	947
Number of countries	107	107	107	107
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AR(1)	0.000790	0.0146	0.00276	1.51e-06
AR(2)	0.0170	0.0776	0.796	0.0290
Hansen	0.529	0.504	0.413	0.333
Number of Instruments	105	105	105	105

Notes: Two-step system GMM estimation where the lag of the dependent variable and the endogenous regressor are instrumented with lags 2 and longer for the transformed equation and lag 1 for the levels equation. AR(1), AR(2) and Hansen report p-values for the respective tests. Finite sample correction applied to all estimations, Windmeijer-corrected cluster–robust errors in parentheses. Estimation run with the command 'xtabond2' in Stata. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: System GMM estimation, non-OECD sample

	(1) LogEmployment	(2) LogAgricultureEmp	(3) LogIndustryEmp	(4) LogServicesEmp
$\text{LogEmployment}_{t-1}$	0.985***			
	(0.0215)			
$\text{LogAgricultureEmp}_{t-1}$		0.932***		
		(0.0342)		
$\text{LogIndustryEmp}_{t-1}$			0.981***	
			(0.0348)	
$\text{LogServicesEmp}_{t-1}$				0.974***
				(0.0149)
IoT100	-0.000183	0.000134	-0.000507	-0.000105
	(0.000821)	(0.00151)	(0.000786)	(0.000832)
Constant	0.0880	1.195**	0.297	0.287*
	(0.276)	(0.578)	(0.291)	(0.149)
Observations	623	623	623	623
Number of countries	71	71	71	71
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
AR(1)	0.00369	0.0839	0.0201	1.32e-05
AR(2)	0.00382	0.204	0.831	0.0186
Hansen	0.936	0.167	0.536	0.939
Number of Instruments	35	35	35	35

Notes: Two-step system GMM estimation where the lag of the dependent variable and the endogenous regressor are instrumented with lags 2 and longer for the transformed equation and lag 1 for the levels equation, and instruments are collapsed. AR(1), AR(2) and Hansen report p-values for the respective tests. Finite sample correction applied to all estimations, Windmeijer-corrected cluster–robust errors in parentheses. Estimation run with the command 'xtabond2' in Stata. *** p<0.01, ** p<0.05, * p<0.1.