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The Internet of Things and economic growth in a panel of countries

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ABSTRACT

Is the world on the cusp of a fourth industrial revolution driven by technological developments in ICT including artificial intelligence and the Internet of Things (IoT)? This paper focuses on IoT and how it might affect economic growth. We attempt to gauge the potential impact of IoT using: (1) regressions based on current IoT data; and (2) longer run estimates of growth accounting parameters based on those observed in a previous wave of the ICT-revolution. We find that: (a) according to definitions in the literature, IoT is an innovational complementarity to ICT; (b) early data already suggest an economically and statistically significant correlation between IoT connections and TFP growth, implying that an increase of 10 percentage points in the growth of IoT connections per inhabitant is associated with a 0.23 percentage points increase in TFP growth; (c) longer run predictions of the IoT contribution based on a growth-accounting framework suggest a potential global annual average contribution to growth of 0.99% per annum (pa) in 2018–2030, approximately $849 billion pa of world GDP in 2018 prices.

1. Introduction

Many analysts believe that the world is on the threshold of a new era of ICT-enabled innovation. One element of that innovation is developments in communications technology (CT) that enable and create communications networks between machines and the wider internet, termed the 'Internet of Things' (IoT). Manyika et al. estimate a potential economic impact from IoT of $3,900–$11,100 billion per annum (pa) in 2025, driven by: lower prices for hardware; advanced computing; cloud storage; higher speed; and lower costs of connectivity; leading to an increasing number of machines and devices connected to the Internet. Manyika et al. (2015) estimates suggest that IoT will contribute approximately 4–11 percent of total world GDP in 2025.[1]

It is argued that IoT will impact both consumers and industries. The latter will be observed in measured productivity, but the former may not if time-savings, free goods or quality improvements are not (fully) reflected in measured prices. In a 'sources of growth' (i.e. growth accounting) context, productivity effects will occur via two channels. Firstly, via capital deepening (an increase in the capital to labor ratio), as firms invest in connectivity equipment for their machines. Secondly, in the form of total factor productivity (TFP) growth, which may be due to: increased efficiency and optimization in the production process; complementary innovation and the accumulation of comp-lementary (in some cases, unmeasured in output) intangible capital including organizational capital

and spillovers or network effects from the accumulation and deployment of communications capital (Goodridge, Haskel, and Edquist 2018).

Since the Industrial Revolution, major technological breakthroughs have changed how we lead our lives and produce goods and services. These are often defined as General Purpose Technologies (GPT) (Bresnahan and Trajtenberg 1995). According to this view, whole eras of technical change are driven by pervasive technologies with inherent potential for progress and innovational complementarities giving rise to increasing returns to scale. In this framework, IoT can be considered an innovational complementarity based on technical improvements in ICT.

The purpose of this paper is to try to understand how IoT might affect economic development and the potential magnitude of that impact. Our approach is to consider IoT in an historical context and compare it with the diffusion of GPTs during earlier eras of technological change. In doing so, we focus on the diffusion of electric motors during electrification in the early twentieth century and the previous wave of the ICT-revolution in the 1990s.

We employ two methods. First, we use recent cross-country data to test for early evidence of a correlation between IoT diffusion and growth in total factor productivity. Second, we use a growth-accounting approach to simulate a longer run projection of the IoT contribution, based on current estimates of IoT investment and parameters observed during a previous wave of ICT capital accumulation. Thus, we try to answer the following questions: (a) what can we learn about the potential economic impact of IoT based on earlier eras of major technological breakthroughs? (b) in what ways should we expect IoT to affect economic development? (c) is there already evidence of a link between IoT and TFP growth? (d) what forecasts can be made on the potential magnitude of the impact of IoT on growth in value added and TFP?

We find that, first, IoT can be viewed as an innovational complementarity to the ICT-revolution, just like electric motors during electrification in the early twentieth century. Second, we investigate whether we can already observe a correlation between IoT connections and TFP growth using early data. Findings for the electric motor suggest that indirect effects in the early twentieth century were substantial but materialized with a lag. Based on data for 82 countries, we find a strong association between the change in IoT connections per inhabitant and TFP growth, suggesting large effects in the early stages of diffusion. We note that this is consistent with Waverman, Meschi, and Fuss (2005).

Our results suggest that an increase of 10 percentage points in the growth of IoT connections per inhabitant is associated with a 0.23 percentage points[2] increase in TFP growth.[3] We observe an increase in the growth of IoT connections per inhabitant of 30% pa in our sample, implying a 0.69% pa contribution to TFP growth,[4] equivalent to $592 billion based on World GDP of $85,804 billion in 2018 (World Development Indicators Database 2019).[5]

Third, we try to gauge longer run estimates of the IoT contribution by combining initial estimates of current IoT investment with growth-accounting parameters and the investment profile observed in OECD countries during the previous wave of the ICT-revolution. Our analysis distinguishes between the capital deepening and TFP effects of IoT. Of that, the capital deepening effect of IoT turns out to be relatively small. That is because, while the projected rates of IoT investment (and therefore capital services) growth are high, the associated user costs and factor income share will be initially low, since IoT is a new technology. At later stages of diffusion, growth rates in investment and capital services will slow, and IoT user costs and the income share will rise in line with the higher level of the capital stock, with these changes somewhat canceling each other out. Our analysis suggests that the indirect effects of IoT on TFP growth may be considerably larger. Based on data for 1996–2013, Goodridge, Haskel, and Edquist (2018) estimate network effects in TFP that are approximately four times the CT capital services contribution.

Using estimates of current IoT investment and the investment profile observed during the previous wave of the ICT-revolution, based on our preferred benchmark our projection of the IoT contribution is far less than the predictions reported in Manyika et al. (2015). It is however substantial at around 0.99% pa of growth, equivalent to $849 billion of global GDP.[6] Our predicted estimate of TFP growth due to IoT, based on evidence from Goodridge, Haskel, and Edquist (2018), is 0.8%

pa, remarkably close to our econometric estimate. Our analysis shows that the key parameter in forecasting the IoT growth contribution is the starting value for IoT investment, for which no official data are yet available. Thus, our results are quite sensitive to the assumptions made about the initial starting values of IoT investment.

2. Definition and diffusion of IoT

There is a plethora of different definitions for IoT. According to Manyika et al. (2015), IoT is defined as 'sensors and actuators connected by networks to computing systems. These systems can monitor the health and actions of connected objects and machines. Connected sensors can also monitor the natural world, people and animals'. The International Telecommunication Union (2012) use a somewhat different definition: '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'.

An IoT system always includes a machine-to-machine (M2M) connection. Thus, M2M connections are an integral part of IoT. These connections may be based on different technologies including cellular or WiFi. However, according to Höller et al. (2014), M2M solutions do not generally allow for the broad sharing of data or the connection of devices to the Internet. IoT may resemble M2M communication but also refers to the connections of such systems and sensors to the Internet. Moreover, it also includes the use of general Internet technologies.

Figure 1 presents data on global diffusion of licensed cellular IoT connections, 2010–2018.[7] The total number of cellular IoT connections has increased exponentially from 76 million in 2010 to 1,102 million in 2018 (growth of 40% pa). Figure 1 shows that growth has been particularly strong in China, at 66% pa. Chinese cellular IoT connections accounted for 15% of world connections in 2010, and 61% in 2018. Corresponding figures for the US are 28% in 2010 and 11% in 2018. According to Ryberg (2019) the Chinese large-scale adoption of IoT has been driven by investments in connected cars, smart metering, payment terminals, industrial applications and smart cameras. However, there is no information on how many connections that belong to each of these market segments.[8]

Figure 1 shows that IoT connections have been growing more rapidly in China compared to the US in absolute figures. However, Table 1 shows that the level, in terms of IoT per 100 inhabitants, was still higher in the US in 2017. Nevertheless, the rapid growth in Chinese IoT investments mean that the Chinese level in 2017 was higher than in many OECD-countries. Table 1 also shows that Sweden had exceptionally high levels of IoT connections per inhabitant. Moreover, if the annual growth rate in non-OECD countries would have been approximately 23 percentage points higher during the investigated period, they would have reached the same level as OECD-countries in 2017.
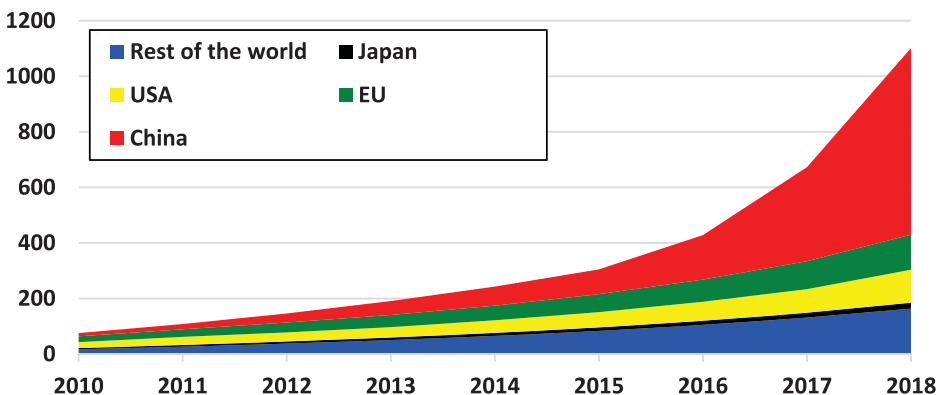

Figure 1. Number of total cellular IoT connections in the world (in million). Source: GSMA Wireless Intelligence Database (2019).

Table 1. Number of IoT connections per 100 inhabitants in different countries.

Country	2010	2011	2012	2013	2014	2015	2016	2017
China	0.8	1.4	2.4	3.6	4.9	7.3	12.2	24.0
France	4.1	5.5	7.3	10.6	12.6	16.0	17.1	22.5
Germany	2.9	3.7	4.9	6.4	8.4	11.2	13.7	16.6
Japan	3.4	4.7	6.1	7.2	8.9	10.1	12.1	13.8
Sweden	24.1	31.8	41.3	53.7	63.2	68.8	88.0	105.8
United Kingdom	5.0	6.4	7.9	8.7	10.4	12.4	15.3	17.6
United States	5.8	7.6	9.4	11.6	13.9	17.3	21.0	27.5
EU countries	4.9	8.7	11.5	14.3	16.9	19.6	23.3	27.7
OECD countries	4.9	8.0	10.4	12.9	15.3	17.8	21.2	25.4
Non-OECD countries	0.6	1.0	1.5	2.0	2.6	3.2	4.1	5.2
All countries	2.5	4.1	5.4	6.7	8.1	9.6	11.5	14.0

Source: GSMA Wireless Intelligence Database (2018).
Note: Non-OECD are the 46 countries included in Table 2. Romania is not included in data for EU-countries. Aggregates are based on unweighted averages.

3. IoT in an historical and GPT context

Apart from some management consulting literature, such as Manyika et al. (2015), as far as we are aware there has been little academic research on the (potential) economic impact of IoT, as it is a recent technological development. There is of course however a wider literature on the economic impact of ICT and its role as a GPT.

According to Bresnahan and Trajtenberg (1995), GPTs are characterized by major technological progress, pervasive use in a range of different industries and the enabling of complementary innovations. ICT has been classified as a GPT (O'Mahony and Vecchi 2005; Rincon, Vecchi, and Venturini 2013). In this framework, IoT can be considered a complementary innovation based on ICT technology.

This suggests the appropriate context of IoT is the ICT literature. Broadly speaking, the literature on ICT considers its economic impact in terms of effects on productivity growth and examines two distinct channels. First, via the contribution of ICT capital deepening, and second, via potential effects on growth in TFP. On ICT capital deepening, much of the focus has been on the measurement of ICT capital, in particular ensuring that quality improvements in ICT capital are adequately reflected in the price indices used to estimate real ICT investment and capital services (see e.g. Jorgenson (2001); Triplett (2004)).

Oliner and Sichel (2000) study the US productivity boom of the late 1990s which they conclude was largely driven by growth in the contribution of ICT capital deepening and efficiency (TFP) gains in ICT production. On links between TFP growth and ICT use, Basu et al. (2004) document the acceleration in labor and total factor productivity growth in the US and contrast it with the deceleration in the UK (and Europe and Japan). They attribute that acceleration to the use of ICT (and complementary co-investments) and its GPT nature. These and other papers in a similar spirit all consider ICT and its economic impact in the historical context of GPTs.

Prior to development in ICT, other examples of GPTs are the steam engine, electrification and the internal combustion engine (Edquist and Henrekson 2006). Although each technological breakthrough is unique, there may be general patterns that can be used to better understand the impact of new technologies.

Many analysts and researchers believe that IoT will have a substantial impact in businesses and among consumers. Moreover, it is argued that effects will be particularly pronounced in manufacturing and other production. Manyika et al. (2015) estimates an economic impact of IoT in manufacturing, hospitals and farms of $1,200–3,700 billion in 2025. The value would arise primarily from energy savings, improvement in labor efficiency, equipment maintenance, inventory optimization and workers health and safety.

A parallel development in economic history is the diffusion of electric motors in the early twentieth century. According to Devine (1983, 371) the most rapid transition in energy was the shift

from steam to electric power in driving machinery. The diffusion of primary electric motor capacity in US manufacturing (1899–1954) was characterized by exponential growth.[9] Total primary electric motor capacity increased from 178 horsepower in 1899 to 74,602 in 1954, a growth rate of 12% pa (Du Du Boff 1979). By 1929, electric motors represented 78% of the total capacity for driving machinery (Devine, 351). The substitution from steam to electric power reduced the energy needed to drive machinery in manufacturing, but more importantly also enabled process innovation and improved factory organization (accumulation of intangible or knowledge capital) which resulted in a wave of TFP growth.

Before the introduction of electricity in manufacturing, energy was provided by steam engines or waterwheels. This meant that all machines in a factory were linked to the same power source through iron and steel 'line shafts'. The entire networks of 'line shafts' were inflexible in the sense that all machines had to be run at the same time. Moreover, if one machine or shaft broke down the whole network of machines was affected.

The first electric motors simply replaced steam engines and continued to turn line shafts. However, it was discovered that large gains could be made by increasing the number of electric motors and cutting down on the shafts. Later, each machine was connected to an electric motor, thus creating a unit drive system. This resulted in large productivity gains as energy was saved and the whole network became less vulnerable to machine breakdowns. Hence, the most important economic effect of the unit drive system came from the reorganization of the machine structure in a factory (Devine 1983).

The process of electrification began in the 1880s both in the US and Europe (Goldfarb 2005; Landes 1969). According to David (1990; 1991) the reorganization of production processes around the electric motor took considerable time. Thus, it was not until half of the mechanical drive system had been electrified in the 1920s that productivity growth started to increase. To support his hypothesis David shows a correlation between the change in the rate of productivity growth from 1909–1919 to 1919–1929 and the ratio of secondary electric motor capacity in 1929 to that capacity in 1919.[10]

Electrification and ICT can be defined as GPTs and electric motors and IoT as complementary innovations to electrification and the ICT-revolution, respectively. Is it then possible to draw conclusions based on the parallel development of these complementary innovations in different time periods?

The literature clearly shows that electric motors had a major impact on production processes in manufacturing. As the number of connections between machines increases it is likely that the early effects of IoT will also be observed in manufacturing and other production including mining and quarrying (Manyika et al. 2015). Moreover, just as the productivity impact of electric motors was partly due to changes in the production process, IoT will also contribute to increased optimization in production. Furthermore, the ability to collect and use data in this optimization process will be important. It also seems reasonable to expect that the rate of technical progress in ICT production will continue at similar rates to those seen in recent economic history and in the case of electric motors (10–20% pa, the approximate rate of quality improvement and price decline in ICT equipment observed in recent decades).

Another insight from electricity is that it took a long time from the first commercial use of electricity before any observed effect on productivity. David argues that it took several decades. Likewise, Solow (1987) famously noted that 'You can see the computer age everywhere but in the productivity statistics', before the productivity boom attributed to the production and use of ICT in the 1990s. However, as we will show, early data already suggest a correlation between IoT connections and growth in TFP.

4. How will IoT affect economic development?

One way of thinking about the impact of IoT is through the framework of growth accounting (Jorgenson and Griliches 1967; Solow 1957).

Broadly, the sources of growth literature can be divided into two approaches: (a) the original neoclassical framework as described in Solow (1957); and (b) endogenous growth theory, to which seminal contributions include those from Arrow (1962), Romer (1986, 1990) and Lucas Jr (1988).

In the neoclassical framework, total factor productivity (TFP) growth is driven by technological change[11] which is determined exogenously and is labor augmenting. Proponents of endogenous growth theory point to the roles of science, innovation, human capital, knowledge accumulation and (technological and knowledge) spillovers in driving technical change and TFP growth, and note that such advances are not costless and are determined endogenously.

Both the neoclassical and endogenous growth frameworks distinguish sharply between the contributions of capital accumulation and TFP growth, both in theory and in measurement. Endogenous growth theory can be thought of as a framework to 'explain' the unexplained TFP residual of the neoclassical framework.

The simple framework we present below is, we believe, consistent with both theories in the sense that it distinguishes between an IoT capital contribution and TFP growth. Our inclusion of spillover or network effects from IoT capital contributing to TFP growth is in the spirit of the endogenous growth tradition; a full optimization model of endogenous IoT investment is beyond the scope of this paper.

The growth accounting framework writes a value added relation between growth rates in V, real value added, K and L, capital and labor services[12] that defines TFP growth as:

$$\Delta \ln V_{i,t} = s_K \Delta \ln K_{i,t} + s_L \Delta \ln L_{i,t} + \Delta \ln TFP_{i,t} \tag{1}$$

where if s_K and s_L are average capital and labor shares over time periods, this relation is consistent with variety of underlying production functions e.g. translog (Diewert 1973).

Factors that might affect TFP growth include: the contribution of unmeasured intangible or knowledge capital (Corrado, Hulten, and Sichel 2009; Marrano, Haskel, and Wallis 2009) including organizational change; technological progress; as well as returns to scale and measurement errors in output and input.

In the case of IoT, the growth accounting framework shows that IoT will affect value added through two channels. The first is the direct effect from capital investments in IoT equipment. The second is that, due to its GPT nature, there may also be indirect effects in the form of spillovers or network effects, complementary formation of intangible organizational capital and a more efficient production process, which shift the production function. Thus some, portion of ΔlnTFP might be driven by IoT capital growth ($s_{IoT}\Delta \ln K_{IoT}$) with factor of proportionality λ so that Equation (1) can be restated as:

$$\Delta \ln V_{i,t} = s_{NK} \Delta \ln K_{NIoT,t} + s_{IoT} \Delta \ln K_{IoT,t} + s_L \Delta \ln L_{i,t} + \lambda s_{IoT} \Delta \ln K_{IoT,t} + \Delta \ln TFP_{NIoT,t} \tag{2}$$

where $s_{IoT}\Delta \ln K_{IoT,t}$ is the IoT capital contribution, $s_{NK}\Delta \ln K_{NIoT,t}$ is the non-IoT capital contribution and $\Delta \ln TFP_{NIoT,t}$ is the component of TFP growth due to non-IoT capital.

5. Empirical evidence: econometric estimates

5.1 Econometric specification

Although there are currently no official data available on investment in IoT equipment at the country level, there are industry data (GSMA 2018; 2019) on the total number of licensed cellular IoT connections. Thus, we estimate a traditional spillovers equation (see, for example Griliches (1973)) that seeks a correlation between TFP growth and IoT connections and interprets the coefficients on regressors as elasticities due to spillovers. We test for that correlation using the following ordinary least squares (OLS) specification based on first differences in order to control for country fixed effects:

$$\Delta \ln TFP_{i,t} = \beta_{IoT} \Delta \ln IoTpop_{i,t} + \beta_{MBB} \Delta \ln MBBpop_{i,t} + \beta_K \Delta \ln K_{i,t} + \beta_{QL} \Delta \ln LS_{i,t} + \delta_t + v_{i,t} \tag{3}$$

where $\Delta \ln TFP_{i,t}$ is the change in TFP in country i, $\Delta \ln IoTpop_{i,t}$ is the change in total cellular licensed IoT

connections per inhabitant and can be viewed as a proxy for the change in intensity of each country's investment in IoT, $\Delta \ln MBBpop_{i,t}$ is the mobile broadband connections per inhabitant which are considered important for economic development (Edquist et al. 2018), $\Delta \ln K_{i,t}$ is the change in log capital services and $\Delta \ln LS_{i,t}$ is the change in log labor services.[13] δ_t are year dummies, which capture common economic shocks, and $v_{i,t}$ is the differenced residual.

We note the following points on our specification. First, we note that there may be an issue of endogeneity. However, we have been unable to find any suitable instrument for IoT connections (already a proxy for the change in IoT capital services) over the large sample of countries for which we estimate. One option could be to lag our independent variable but, as noted in Reed (2015), this does not necessarily address the issue of endogeneity. We are also unable to employ a generalized method of moments (GMM) specification due to the limited length of the panel. However, we do note that, to the extent that instrumental variable (IV) and GMM approaches provide a cross-check on OLS techniques, our alternative approach using growth-accounting parameters does at least provide a cross-check on our econometric results.

Second, our measure of labor input is labor services (LS), which is a composition (or quality) adjusted measure where growth in the hours worked of different composition groups are weighted together according to that group's share in labor compensation. Our measure of TFP growth is also estimated by subtracting the contribution of the same measure of labor services. Thus, we control for the contribution of human capital.

Third, for our baseline estimates we take first differences and in our robustness checks we also present results based on three-year differences. In taking these differences we are losing degrees of freedom in our estimation. However, we base our specification on differences because of index number problems and difficulties in the interpretation of a model based on levels where, for example, the concept of the level of capital services is unclear (Inklaar and Timmer 2008). The taking of first differences also allows us to control for country fixed effects. The taking of longer (three-year) differences has greater consequences for degrees of freedom, but we feel provides a useful robustness check by removing annual noise from the data and being consistent with longer-run correlations that occur with a lag, since instant spillover transmission appears unrealistic.

5.2 Econometric analysis: data

In our econometric analysis, country data on growth in TFP and capital and labor services are from the Total Economy Database (2018). Labor services have been constructed by aggregating the change in labor quantity and quality.[14] The former is based on total hours worked (whenever available) or total persons engaged. The latter is based on a measure of the changes in the composition of the workforce, which is based on underlying data on employment and wages by educational attainment.

Country-level data on licensed IoT connections, mobile broadband connections and population are from GSMA Wireless Intelligence Database (2018), for years 2010–2017.

Table 2 shows the countries included in our regressions.

Table 3 presents descriptive statistics for the variables used in the analysis. In total we have data for 82 countries over the period 2010–2017.[15] Table 3 also divides our sample into OECD and non-OECD countries. In general, average growth in IoT connections per inhabitant was higher in non-OECD countries, but as shown in Table 1 the level is still considerably higher in the OECD. If the annual growth rate in non-OECD countries was approximately 23 percentage points higher on average during the investigated period, they would have reached the same level as OECD-countries in 2017.

5.3 Results: econometric analysis

In Section 5.1 we specified our regression based on first differences in order to control for country specific fixed effects. After removing extreme outliers from our sample, we find a significant

Table 2. OECD and non–OECD countries included in our regression.

OECD countries (36)	Australia, Austria, Belgium, Canada, Chile, Czech Republic, 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
Non–OECD countries (46)	Argentina, Armenia, Bahrain, Bangladesh, Bolivia, Brazil, Bulgaria, Cambodia, China, Colombia, Costa Rica, Croatia, Cyprus, Dominican Republic, Ecuador, Egypt, Ghana, Guatemala, Hong Kong, India, Indonesia, Jamaica, Kazakhstan, Malawi, Malaysia, Malta, Morocco, Pakistan, Peru, Philippines, Qatar, Russia, Saudi Arabia, Senegal, Singapore, South Africa, Sri Lanka, Taiwan, Tanzania, Thailand, Tunisia, Uganda, Ukraine, United Arab Emirates, Uruguay, Vietnam

Note: 36 OECD, 46 Non-OECD, total 82 countries.

Table 3. Descriptive statistics (2010–2017).

Variable	Mean	St. Dev.	Min	Max	No. obs
All countries					
Log change in total factor productivity ($\Delta lnTFP$)	0.002	0.02	−0.07	0.08	574
Log change in IoT connections per inhabitant ($\Delta lnIoTpop$)	0.30	0.19	−0.08	1.82	574
Log change in capital services (ΔlnK)	0.04	0.03	−0.03	0.13	574
Log change labor services ($\Delta lnQL$)	0.02	0.03	−0.11	0.17	574
Log change mobile broadband connections per inhabitant ($\Delta lnMBBpop$)	0.26	0.26	−0.06	2.07	574
OECD-countries					
Log change in total factor productivity ($\Delta lnTFP$)	0.003	0.02	−0.06	0.06	252
Log change in IoT connections per inhabitant ($\Delta lnIoTpop$)	0.24	0.13	−0.04	1.17	252
Log change in capital services (ΔlnK)	0.02	0.02	−0.03	0.12	252
Log change in labor services ($\Delta lnQL$)	0.01	0.02	−0.04	0.08	252
Log change mobile broadband connections per inhabitant ($\Delta lnMBBpop$)	0.14	0.11	−0.06	0.82	252
Non-OECD countries					
Log change in total factor productivity ($\Delta lnTFP$)	0.002	0.02	−0.07	0.08	322
Log change in IoT connections per inhabitant ($\Delta lnIoTpop$)	0.35	0.21	−0.08	1.82	322
Log change in capital services (ΔlnK)	0.05	0.03	−0.02	0.13	322
Log change in labor services ($\Delta lnQL$)	0.02	0.03	−0.11	0.17	322
Log change mobile broadband connections per inhabitant ($\Delta lnMBBpop$)	0.35	0.31	−0.05	2.07	322

Note: 36 OECD, 46 Non-OECD, total 82 countries.

correlation between TFP growth and the log change in IoT connections per inhabitant. Analysis show that our regression results are primarily sensitive to the inclusion of Syria in our sample.[16] That said, if we retain Syria and use robust regression techniques, we get the same results as in Table 4 below, see Appendix D.

Table 4 presents our results. They show that TFP growth is positively associated with the change in log IoT connections per inhabitant at the 5 percent level. Once we include MBB connections per inhabitant the results imply that a 10 percentage points (pp) increase in the growth of IoT connections per inhabitant is associated with 0.23 pp growth in TFP.

We also provide estimates using three-year differences. Based on firm-level data, Brynjolfsson and Hitt (2003) found that longer differences generated a larger and stronger correlation between ICT and TFP growth and Griliches and Mairesse (1999) argue that longer differences lower (classical) measurement error. The results based on three-year differences are positive and significant at the 5 percent level, but with larger coefficients.[17] One possible explanation could be that productivity effects from IoT investment materialize with a lag, perhaps because, like broader ICT, IoT investments require complementary investments in intangibles, such as vocational training and organizational capital, to reap the productivity effects from reorganization of production. Another potential explanation is that longer differences attenuate measurement error.[18]

Table 5 presents the correlation separately for OECD and non-OECD countries. The IoT coefficient is similar and is significant at the 10 percent level for both. The decreased significance could be due to reduced sample size. Notice that the statistical precision of the effect of labor and capital services is less for OECD countries, and the labor coefficient is no longer negative.

Table 4. Regressions investigating the relationship between TFP growth and the change in the log of cellular licensed IoT connections per inhabitant and the log of mobile broadband connections per inhabitant.

	Dependent variable: TFP growth ($\Delta \ln TFP$)			
	First differences	First differences	Three years differences	Three years differences
ΔLog of Licensed IoT connections per inhabitant ($\Delta lnIoTpop$)	0.026** (0.010)	0.023** (0.009)	0.036** (0.015)	0.031** (0.014)
ΔLog of mobile broadband connections per inhabitant ($\Delta lnMBBpop$)		0.01* (0.005)		0.01 (0.007)
ΔLog labor services ($\Delta lnQL$)	−0.19** (0.072)	−0.19*** (0.073)	−0.15 (0.108)	−0.16 (0.109)
ΔLog capital services (ΔlnK)	−0.11* (0.058)	−0.12** (0.058)	−0.11* (0.063)	−0.13* (0.064)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.18	0.19	0.21	0.22
Number of observations	574	574	410	410

Note: Cluster robust standard errors are presented in parenthesis. ***, **, *indicate statistical significance at the 1%, 5% and 10% levels, respectively. Countries with extreme outliers for the dependent variable were removed from the sample.

On the magnitudes, or economic significance, of our results, those based on first differences suggest that a 10 percentage points increase in the growth of IoT connections per inhabitant is associated with approximately 0.23 percentage points of growth in TFP over the investigated period. In our data, we observe growth in IoT connections per inhabitant of 30%, implying a contribution to GDP of approximately $592 billion pa.[19] Note that this is far short of effects predicted by Manyika et al. of $3,900–$11,100 billion pa in 2025.

An additional check on the magnitudes can be gleaned from a comparison with Waverman, Meschi, and Fuss (2005) who look at the relation between mobile penetration and economic growth using a panel of 38 developing countries, 1996–2003. They have a simultaneous equation system, but for our purposes the key is that they regress the level of output on capital, labor and the log level of mobile penetration per 100 persons. In their data the average mobile penetration level is 7.84 and they find that a doubling of this level is associated with a rise in output (net of capital and labor) of 10%. It should be noted that they dismiss this effect as being too large. To relate this to our work, note first that we use the number of IoT connections per 100 citizens, with an average value of 0.6 in 2010 to 5.2 in 2017 for non-OECD countries (see Table 1). Connections are different to those having a device (see below) and since some connections might not be in the business area, normalizing on population, and not some measure of business capital stock might be desirable.

Table 5. Regressions investigating the relationship between TFP growth and the change in the log of cellular licensed IoT connections per inhabitant and the log of mobile broadband connections per inhabitant.

	Dependent variable: TFP growth ($\Delta \ln TFP$)			
	OECD	OECD	Non-OECD	Non-OECD
ΔLog of Licensed IoT connections per inhabitant ($\Delta lnIoTpop$)	0.021* (0.011)	0.017* (0.010)	0.023* (0.012)	0.023* (0.012)
ΔLog of mobile broadband connections per inhabitant ($\Delta lnMBBpop$)		0.03 (0.020)		0.008 (0.006)
ΔLog labor services ($\Delta lnQL$)	0.06 (0.080)	0.03 (0.081)	−0.25*** (0.081)	−0.25*** (0.081)
ΔLog capital services (ΔlnK)	−0.11 (0.080)	−0.14* (0.082)	−0.12 (0.079)	−0.12 (0.076)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.14	0.17	0.23	0.24
Number of observations	252	252	322	322

Notes: Cluster robust standard errors are presented in parenthesis. ***, **, *indicate statistical significance at the 1%, 5% and 10% levels, respectively. Countries with extreme outliers for the dependent variable were removed from the sample.

To compare results, a doubling of average IoT penetration in our dataset would take penetration from 5.2 to 10.4, a rise of 0.69 log points for non-OECD countries. With a coefficient of 0.023 in Table 5, this is a rise in TFP growth of 1.6%. A glance at Table 1 shows that penetration has indeed doubled in two years, 2010–2012 and then three years 2012–2015. With an average growth rate of TFP (see Table 3) of 0.2% per year, this rise drastically overstates actual TFP growth, in these early years at least. Of course, as time passes the years which it takes to double connections might get longer, although one might argue that with more devices connections might rise non-linearly (roughly to the square value of devices). Thus, it is likely that our estimate is too high, reflecting early years effects and not accounting for decreasing returns to technology.

Appendix D shows our results are robust to two robustness checks, namely using robust regression methods and levels regression (for which a stronger set of assumptions on the data are needed).

6. Empirical evidence: growth accounting

To further test the robustness and provide a cross-check on our econometric results, we turn to growth accounting methods. Using a traditional sources of growth framework, as applied in for instance EUKLEMS (Timmer, O'Mahony, and van Ark 2007), we predict an IoT contribution using current estimates of IoT investment and parameters observed in a previous wave of the ICT revolution.

The underlying dataset is that constructed for Goodridge, Haskel, and Edquist (2019), including national accounts downloaded from OECD.Stat, and derived growth-accounting data, for fourteen OECD countries: the US (1990–2013) and 13 EU countries (1996–2013).[20] For more details on the underlying dataset, see Goodridge, Haskel, and Edquist (2019) and the data appendix F to this paper.

6.1. Framework

As set out above, the total contribution of $\Delta \ln K_{IoT}$ consists of two effects (a) the share-weighted IoT contribution ($sK_{IoT} \Delta \ln K_{IoT}$)[21] and (b) any spillover effects from $\Delta \ln K_{IoT}$ to $\Delta \ln TFP$, which we express as $\lambda sK_{IoT} \Delta \ln K_{IoT}$.[22]

$$\text{Total IoT contribution} = sK_{IoT}\Delta \ln K_{IoT,t} + \lambda sK_{IoT}\Delta \ln K_{IoT,t} \tag{4}$$

To predict $\Delta \ln K_{IoT}$ over the coming decade, we need a starting value of K_{IoT}, call that $K_{IoT,0}$, for which we use an initial value of real investment, $I_{IoT,0}$, since IoT is a new technology. We then apply the perpetual inventory method to get K_{IoT} where $K_{IoT} = I_{IoT} + (1-\delta)^t K_{IoT,0}$. To do this, we need, in turn δ and predicted future real investment in *IoT*, call that $I_{IoT} = P_{I,IoT} I_{IoT}/P_{I,IoT}*$ where $P_{I,IoT}*$ is an IoT investment deflator. To measure the share, $P_{K,IoT}K_{IoT}/PvV$, we need $P_{K,IoT}$ for which we use the Hall-Jorgenson user-cost relation $P_{K,IoT} = P_{I,IoT}(r+\delta-\pi)$. Finally, we need an estimate of λ.[23]

6.2 An initial value for I_{IOT} and K_{IOT} in 2018

It turns out that our analysis depends critically on the initial value for real IoT investment and capital stock and thus we discuss this first.[24]

In order to forecast IoT capital services and the IoT contribution, we require an estimate of investment in IoT equipment. No national accounts data are currently available but we have located two estimates of global IoT investment from the management consulting literature and a benchmark from Ericsson Annual Report (Ericsson 2018).

First, Gartner[25] estimate worldwide IoT 'endpoint spending' of $2,085 billion in 2018. Second, based on data for 53 countries, IDC[26] estimate global IoT spend of $646 billion in 2018. We note the very large disparity between these two estimates. Third, from Ericsson (2018) we know that, in

2018, the ratio of Ericsson sales for the market area 'Emerging business and other' (including, but not exclusively, sales of IoT technologies) to the market area 'Networks' was 6 percent.[27]

However, first, from our communication with Gartner we know that theirs is an estimate of the full asset value of all capital connected to IoT equipment e.g. therefore including the building, machine or vehicle to which the sensor is attached. Thus, if all tangible capital equipment were connected, this definition would assign the entire contribution of tangible capital to IoT. Obviously, this is not correct and, without any distinct estimate for investment in IoT equipment and systems, we are unable to assess the impact and potential impact of IoT based on this investment estimate.

Second, based on an estimate of global GDP of $85,804 billion in 2018 (World Development Indicators Database 2019), the IDC estimate of IoT spend accounts for 0.8% of world GDP. Note the Gartner estimate implies that IoT spend accounts for 2.4% of world GDP, which seems particularly large.

Based on forecast EU-13 GDP of $14,085 billion in 2018,[28] the IDC and Gartner estimates imply IoT investment of $106 billion and $342 billion in the EU-13 in 2018. To put these estimates in context, we estimate EU-13 investment in communications (CT) equipment of $45 billion in 2018.[29] Thus the IDC estimate applied to EU-13 data is more than double estimated EU-13 CT investment, while the Gartner estimate is almost eight times estimated EU-13 CT investment.

Given these implied IoT investment figures, it is worth considering under which headings IoT investment will be recorded in national accounts classifications. If IoT investment only consists of sensors and other forms of communications equipment, then IoT investment is some subset of CT investment. However, if IoT investment also consists of investments in IT hardware and software,[30] and we conjecture that it does, then the correct benchmark is a broader definition of ICT capital.

EU-13 investment in broader ICT capital (including software) in 2018 is estimated at $394 billion.[31] The IDC estimate implies that 27% ($106 billion) of this is investment in IoT. The Gartner estimate implies that 87% of EU-13 ICT investment in 2018 represents investment in IoT, which supports our view that this is an overestimate.

In our simulation, summarized in Table 6 below, we shall use these estimates to form two alternative assumptions for the initial value of IoT investment and therefore the initial IoT capital stock in 2018. First, we take the IDC estimate as our baseline, and assume an initial value for nominal IoT investment of $106 billion in the EU-13 in 2018 (corresponding to 27% of EU-13 ICT investment). We note however that this estimate is only plausible if IoT investment also consists of substantial software investment. We consider that it almost certainly does, but we shall test whether it is a plausible estimate using a predicted growth-accounting analysis, based on a framework consistent with that used in, amongst others, EUKLEMS (Timmer, O'Mahony, and van Ark 2007) and other KLEMS studies (e.g. WorldKLEMS, AsiaKLEMS etc.).

To test the robustness of our result, second we shall use data from the Ericsson report that between 0 and 6% of CT equipment spend is in IoT, implicitly applying the much more conservative assumption that IoT investment is a subset of CT investment. We therefore assume that 3% of EU-13 CT investment in 2018 is spent on IoT, corresponding to an initial value for IoT investment of $1.36 billion in the EU-13 in 2018. Thus, we test the sensitivity of our results to the assumed initial value for IoT investment.

6.3 Other data

These are nominal data, so we require a further assumption to estimate real IoT investment and the real IoT capital stock in the EU-13 in 2018 and future years. Our estimate of price change is based on the US national accounts deflator for investment in CT equipment, based in 2011 (2011 = 1) and ending in 2013. To extend the index forward, we first estimate average price change over the (1996–2013) series at −4.2% pa, and extend the series forward using that average change. Second, we test sensitivity to this assumption by assuming a faster decline based on that observed in Byrne and Corrado (2015) at approximately 10% pa. Implicitly this assumes technical progress in communications equipment over the next two decades occurs at a similar rate to the past two decades.

Table 6. Projection: IoT contribution.

Baseline	K^{IoT} start value	$\Delta ln I^{IoT}$ (log point growth)	$\Delta ln P_I^{IoT}$ (log point growth)	δ^{IoT}	asK^{IoT}	$\Delta ln K^{IoT}$	$Con\Delta ln K^{IoT}$ (incl. spills)
IDC estimate: 27% of $P_I I^{ICT}$ (2018) = $106bn	$141 bn	17%	−4.2%	0.115	0.80%	30.7%	0.19% (0.99%)
Robustness Checks							
(1) Vary start value Ericsson: 3% of $P_I I^{ICT}$ (2018) = $1.4bn	$1.8 bn	17%	−4.2%	0.115	0.01%	30.7%	0.002% (0.013%)
(2) Vary DlnI^{IoT} and DlnP_I^{IoT}							
(a) Double $DlnI^{IoT}$ (Initial value based on Ericsson)	$2.5 bn	34%	−10%	0.115	0.01%	41.0%	0.004% (0.02%)
(b) Double $DlnI^{IoT}$ (Initial value based on IDC)	$194 bn	34%	−10%	0.115	0.98%	41.0%	0.34% (1.74%)
(3) Vary δ^{IoT} (Initial value based on IDC)							
(a) Halve $\delta^{IoT} = 0.0575$	$141 bn	17%	−4.2%	0.0575	0.66%	32.5%	0.17% (0.86%)
(b) Double $\delta^{IoT} = 0.23$	$141 bn	17%	−4.2%	0.23	0.99%	27.4%	0.22% (1.12%)

Source: Authors calculations based on: estimates of IoT investment from (a) IDC and (b) Ericsson annual reports; and parameters observed in growth-accounting dataset constructed for Goodridge, Haskel, and Edquist (2019).

Note: Column 1 provides details of which parameter we vary; column 2 is the starting value for the IoT capital stock; column 3 is the assumed growth rate in real IoT investment; column 4 is the assumed rate of price decline for IoT assets; column 5 is the assumed rate of depreciation for IoT technology; column 6 is the average predicted IoT income share; column 7 is the average predicted growth rate in IoT capital services; column 8 is the average predicted IoT contribution including estimated spillovers or network effects in parentheses based on estimates in Goodridge, Haskel, and Edquist (2018) and estimated as the contribution times 4.1. Columns 6–8 are average predicted values for years 2018-2030. Note that column 6 multiplied by column 7 does not give the value in column 8 as the average of a product is not the same as the product of two averages.

Doms (2005) notes that such progress in communications technology has exceeded that implied by Moorés Law.[32] The rate of price decline implicitly feeds into projected real investment and user costs and therefore the IoT contribution.[33]

To estimate future IoT capital services growth, we must forecast real IoT investment growth. In our baseline assumption, we assume that real IoT investment grows at the same rate as that observed for real CT investment in the US during the ICT investment boom of the late 1990s (17% pa, see Appendix G). We test sensitivity to this assumption by assuming even faster investment growth, doubling the growth rate to 34% pa, which is also consistent with faster falls in IoT equipment prices. Moreover, we choose a depreciation rate for IoT the same as that for CT equipment of 0.115,[34] but test sensitivity to this assumption by halving and doubling that rate.[35]

To estimate user costs, we have alternative assumptions for the rate of depreciation (δ) and the assumed rate of price decline implies an estimate for the capital gains term (π). We require an additional assumption for the net rate of return (r). This is uncertain but we choose an estimate of 10% based on approximately that observed in the OECD-14 countries in our growth-accounting dataset (1996–2013). However, sensitivity analyses show that the forecast is not sensitive to this parameter.

To forecast the IoT income share we also need to forecast nominal value-added for the denominator. We have an estimate of EU-13 value-added in 2013 of $12,750 billion. We extend that forward assuming future growth of 2% pa, based on the mean growth rate observed in 2009–2013.

Finally, for spillovers or network effects, we need a value of λ for which we adopt 4.1, as estimated in Goodridge, Haskel, and Edquist (2018).[36]

6.4. Results: growth accounting

The results of this exercise are presented in Table 6, with a baseline estimate and alternative estimates based on variations to underlying assumptions, as discussed above. In the baseline, based

on our benchmark from IDC, the average direct contribution of IoT to growth is 0.19% pa (2018–2030). If we multiply the IoT capital contribution by 4.1, we get the spillover effect estimated in Goodridge, Haskel, and Edquist (2018). Thus, the average total IoT contribution to growth becomes 0.99% pa (2018–2030). Applied to global GDP, this translates to a contribution to world output of approximately $849 billion pa in 2018 prices, far less than the $3,900–$11,100 billion pa predicted in Manyika et al. (2015). This estimate relies on the assumption that 27% of ICT investment in 2018 represents investment in IoT, which may be a bold one. We note however, that the implied contribution to TFP growth from this estimate is 0.8% pa, quite close to the 0.69% pa estimated in our econometric analysis.

To test the robustness of this result, we perform the same analysis using some alternative assumptions. First, we use the estimate of IoT investment implied by the Ericsson Annual Report (Ericsson 2018). That gives an average IoT capital contribution of 0.002% pa, which is small. Including an estimate of network effects on TFP, the total effect is 0.013% pa. This translates to a contribution to global GDP of just $11 billion pa, which seems to support our baseline assumption that IoT investment consists of broader investments in ICT than solely CT equipment.

In the remaining panels, we use faster price changes (and therefore faster real investment and capital services growth), which raises the contribution, substantially so with a higher baseline and alter depreciation rates (which do not change the contribution so much).

We note that, based on the Ericsson data point, despite assumed fast growth in real IoT investment, and thus projected fast growth in IoT capital services, the implied total contribution remains relatively small (although similar in magnitude to the contribution of CT equipment observed in the EU (2008–2013, see appendix G)). Assuming faster growth in real investment, the IoT capital contribution based on the IDC benchmark is larger at 0.34% pa, which is comparable to the ICT capital contribution observed in the US (2001–2007) and EU-13 (1996–2007) (see appendix G).

In all cases, the IoT income share is initially small since it is new capital/technology, and rises gradually as the accumulated stock grows. As the technology matures, real investment and capital services slow, thus somewhat canceling out the effect of a growing income share. As shown in Table A5 (see appendix G), in the longer run, as growth in investment approaches a steady state, the income share will similarly decline to a long run level.

The above exercise simulates the IoT contribution using alternative estimates of IoT investment with investment growth and price parameters based on observations during previous waves of ICT capital accumulation. A genuine sources of growth decomposition would require data on investment and prices for IoT equipment (important IoT hardware include micro-electromechanical systems sensors (MEMS) and radio-frequency identification tags (RFID)) which are not currently available. Data for future years are also obviously not currently available.

As well as the initial value for IoT investment, Table 6 shows that the other key parameter is the assumed growth rate of real IoT investment, which depends on the growth rate in nominal investment and the rate of price decline and therefore technical progress in IoT technologies. On prices, according to Manyika et al. (2015), the price of MEMS sensors fell by 30–70%, 2010–2015, a rate of approximately 6–14% pa. This indicates rapid technological progress in the production of IoT equipment, at a rate similar to wider telecommunications equipment. Byrne and Corrado (2015) estimate price falls in telecommunications equipment of approximately 10% pa over the period 1985–2009. The last four decades have also seen technical progress and price falls in broader ICT capital, at comparable rates, which have encouraged waves of ICT investment and productivity growth.

7. Conclusions

This paper has investigated the potential economic impact of IoT by placing it in an historical context. Based on the general-purpose technology (GPT) literature, IoT can be viewed as an innovational complementarity to the ICT-revolution. Thus, technical improvements in ICT-technology have provided

the technological possibility to connect machines with each other and to the Internet, which is a pre-requisite for an IoT system.

Just like electric motors in the early twentieth century, IoT connections have diffused rapidly in many countries. IoT systems are also able to generate large amounts of data that can be used to improve optimization of production. Data collection to the same extent was not possible during the diffusion of electric motors and provides additional potential for productivity increases from IoT.

However, while it took considerable time for the productivity effects from electric motors to materialize, using early data we already find a strong association between IoT connections per inhabitant and TFP growth once we control for capital, labor (including labor composition and therefore human capital) and mobile broadband connections. Our findings suggest that an increase of 10 percentage points in the growth of IoT connections per inhabitant is associated with a 0.23 percentage points increase in TFP growth. We observe growth in IoT connections per inhabitant of 30% pa in our sample, implying a contribution to TFP growth of 0.69% pa, a large effect. This is equivalent to a contribution of $592 billion based on world GDP in 2017.

Using estimates of current IoT investment and the investment profile observed during the previous wave of the ICT-revolution, based on our preferred benchmark our projection of the IoT contribution is far less than the predictions reported in Manyika et al. (2015). It is however substantial at around 0.99% pa of growth, equivalent to $849 billion of global GDP in 2018.[37] Our predicted estimate of TFP growth due to IoT, based on evidence from Goodridge, Haskel, and Edquist (2018), is 0.8% pa, remarkably close to our econometric estimate. Our analysis shows that the key parameter in forecasting the IoT growth contribution is the starting value for IoT investment, for which no official data are yet available.

Our econometric analysis based on early data suggest that the indirect effects of IoT on TFP may be very large in these initial stages of diffusion. Similarly, our previous work in Goodridge, Haskel, and Edquist (2018) suggests network effects from CT capital on TFP growth approximately four times larger than the direct capital contribution. Thus, it is possible that relatively small investments in IoT equipment will have large indirect effects on economic development. However, we note that (a) the regression coefficient may include an upward bias due to early year effects and (b) that the observed growth rate in IoT connections may be particularly high in early years (although growth in connections may remain high as connections rise as approximately the square of the number of users). Therefore, we consider our estimates of the IoT contribution to TFP growth of 0.69 (econometric) to 0.8% pa (growth-accounting) as an upper bound.

Notes

1. Manyika et al. (2015) base their estimates on a World Bank projection for global GDP of $99,500 billion in 2025.
2. A 0.23 percentage points increase in TFP growth is equivalent to a contribution of $197 billion based on world GDP in 2018.
3. We note that population may not be the correct variable upon which to normalise. A measure of capital units seems more appropriate, but such data were not available.
4. All growth rates in this paper are calculated as change in log points.
5. It should be mentioned that the casual links have not been investigated further. Thus, we assume that IoT investment affects growth in TFP and output, and not the reverse.
6. We note that our estimate of 0.99 percent is an upper bound (see Table 6)
7. Data are from the GSMA Intelligence database, the definitive source of mobile operator data. With over 26 million individual data points, the service provides coverage of the performance of all 1400+ operators and 1200+ mobile virtual network operators across 4400+ networks, 65 groups and 237 countries and territories worldwide from 1979–present. All reported data are directly linked back to its source. GSMA estimates are of cellular IoT connections. Unfortunately, data on IoT connections based on WiFi were not available at a country level at the time of writing.
8. We also find that our regression results for IoT connections per inhabitant (see Table 4) remain robust at the 5% level once China is excluded from our sample.
9. Primary electric motors were those driven by purchased electricity.
10. Secondary electric motors were driven by generators and prime movers within the factory itself.

11. In practice, the TFP residual will include all contributions not incorporated into the measurement of factor (labor and capital) inputs, therefore including, as well as technical progress, any change in the efficiency with which those factor inputs are combined as well as the contributions of human and knowledge capital if they are not embodied in the measurement of labor (i.e. quality-adjusted) and capital (i.e. including intangible capital) services, respectively.

12. Where labor services are a measure of quality (or more accurately, composition)-adjusted labor input thus incorporating the contribution of human capital to economic growth. Measured capital services are analogously composition-adjusted.

13. Labor services incorporate the change in labor input due to changes in the quality, or more accurately, composition, of the workforce. The contribution of labor services in a growth-accounting context therefore captures the contribution of changes in human capital. Composition adjusted labor services are constructed analogously to composition adjusted capital services. The methodology for estimating capital services is summarised in Appendix A.

14. Appendix B shows that our regressions are robust to including only labor quantity or both labor quantity and quality.

15. Due to extreme outliers in our dependent variable (i.e. TFP growth), the following countries were excluded from out dataset: Kuwait, Moldova, Kyrgyzstan, Syria, Trinidad and Tobago, Venezuela, Yemen and Zimbabwe. If these extreme outliers are not excluded, the IoT per inhabitant variable is insignificant in our regressions (see Section 5.3). We define an extreme outlier as an observation at least 3 interquartile ranges below the first quartile (Q1) or at least three interquartile ranges above the third quartile (Q3).

16. According to the Worldwide Governance Indicators (2019), Syria is a very politically unstable country, emphasized by very negative TFP growth for a number of adjacent years. Appendix C plots the change in TFP and IoT connections per inhabitant both with extreme outliers included and excluded.

17. Based on the seemingly unrelated regressions command in Stata, i.e. sureg we can reject the null hypothesis that the coefficients in the two different equations are equal at the 1% significance level.

18. It is worth noting that the coefficient on labor services is negative and significant based on first differences, but not based on three-year differences. Appendix E plots the change in TFP and labor services based on first and three-year differences.

19. Based on world GDP of $85,804 billion in 2018 (World Development Indicators Database 2019).

20. EU-13 countries are: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Ireland, Netherlands, Portugal, Spain, Sweden and the United Kingdom.

21. For more details on how to estimate K and s_K, see Appendix A.

22. We note that quantifying this spillover or network effect is the most uncertain aspect of our analysis. Our estimate of network effects based on data for 1996–2013 (estimated in Goodridge, Haskel, and Edquist (2018); a period of increasing investment in mobile technologies) may differ greatly from network effects in future periods of increasing investment in IoT technologies. As set out in the model presented in Goodridge, Haskel, and Edquist (2018), the capital term must be share-weighted as spillovers require users to be connected to the network.

23. Based on Goodridge, Haskel, and Edquist (2018) λ can be estimated as $\lambda=(\gamma/(1-\gamma)=4.1$. According to Goodridge, Haskel, and Edquist (2018) γ is approximately equal to 0.8.

24. We need data on nominal investment in other inputs in 2018 to start this process, which we interpolate from our latest data in 2013 as follows. From Goodridge, Haskel, and Edquist (2019), we have data on nominal investment in communications (CT) equipment investment and broader ICT capital in the US and EU-13 up to 2013, with EU values converted to USD using OECD purchasing power parity (PPP) data. In 2013, EU-13 investment in CT equipment stood at $43 billion. We use the growth rate in EU-13 nominal CT investment (2009–2013) to impute EU-13 nominal CT investment from 2014 to 2018, such that we estimate EU-13 CT investment of $45 billion in 2018. Investment in broader ICT capital (including software) in the EU-13 was $339 billion in 2013. An extrapolation to 2018 using the same method gives an estimate of EU-13 ICT investment of $394 billion in 2018.

25. https://www.statista.com/statistics/485252/iot-endpoint-spending-by-category-worldwide/

26. https://www.idc.com/getdoc.jsp?containerId=IDC_P29475

27. 6% represents an upper bound as our conversations with the relevant team at Ericsson confirm that the majority of the revenues in 'Emerging business and other' are licence fee payments.

28. Extrapolated from $12,750 billion observed in 2013 national accounts data for the EU-13, downloaded from OECD.Stat, and the growth rate observed in 2009–2013 (2%).

29. Extrapolated from observed official CT investment of $43 billion in the EU-13 in 2013 (Goodridge, Haskel, and Edquist (2019); downloaded from OECD.Stat) and a growth rate of 1.2% pa observed in 2009–2013 (estimated as change in natural log).

30. Note, investments in data also fall in the category of software (and database) investment in the national accounts nomenclature.

31. Extrapolated from observed ICT (including software) investment of $339 billion in 2013 (downloaded from OECD.Stat) and a growth rate of 3% pa observed in 2009–2013 (estimated as change in natural log).

32. Moore's Law implies that the real volume of ICT input (due to quality change) doubles in approximately 18–24 months.
33. We note that faster price falls would have an endogenous impact on investment and output, the magnitude of which depends upon the elasticities of demand, which we are unable to predict with any accuracy.
34. The same rate as used in EUKLEMS (Timmer, O'Mahony, and van Ark 2007) and also Goodridge, Haskel, and Edquist (2019).
35. Note, doubling the rate results in an assumed rate of deprecation of around 0.23, closer to rates typically assumed for IT hardware (around 0.33) and software (around 0.4), which may be more appropriate if IoT investment also consists of some investments in IT hardware and software.
36. Note Goodridge, Haskel, and Edquist (2018) estimate network effects over a period (1996–2013) of increasing (predominantly mobile) connections between people. We note that the magnitude and impact of network effects between machines may differ. Since machines can make many connections simultaneously, it may be that network effects are larger in the context of IoT connections. Alternatively, it may be that network effects between machines have less impact than those between people.
37. We note that our estimate of 1.0 percent is an upper bound (see Table 6)
38. Results are available upon request.

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Disclosure statement

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Appendices

A: measurement of capital services

Capital (and analogously, labor) services are measures of input that account for factor composition. In the case of capital, capital services allow an aggregation across heterogenous assets which accounts for the differences in the gross rate of return and marginal product for different assets.

Applying a geometric rate of deterioration (and depreciation), and assuming all assets of each type are perfect substitutes (Jorgenson 1963), estimates of the productive stock for each asset can be derived using the standard perpetual inventory method (PIM):

$$K_{i,t} = I_{i,t} + (1 - \delta_i)K_{i,t-1} \tag{A1}$$

where *i* is the asset type, *I* is real investment, *K* the real productive stock, and δ a geometric rate of deterioration. As vintages are aggregated in efficiency units, the estimated stock is directly *proportional* to the real quantity of capital services it is capable of producing.

To allow for different gross rates of return to each asset in the aggregate, assets are aggregated as a superlative index with weights (s) based on factor incomes of nominal capital services:

$$S_{Kjt} = \left(\frac{P_{Kj}K_j}{P_K K}\right)_t, \quad \bar{s} = \frac{(s_t + s_{t+1})}{2}, \quad \sum_i s_{K_{it}} + \sum_j s_{K_{jt}} = 1, \tag{A2}$$

$$P_{Ki} = P_{Ii}(r + \delta_i - \pi_i) \tag{A3}$$

where s are shares of capital compensation for asset *i*, averaged over the current and previous period. P_k are the price of capital services, estimated using information on the investment price (Pi), asset-specific deprecation rates (δ) and the capital/holding gain/loss according to the Hall and Jorgenson (1967) user cost formula.

B: regressions based on labor quantity and quality

In our base case regression, we include labor services as one of the explanatory variables. Tables A1 and A2 show that our regressions are robust once we include only labor quantity and once we include both labor quality and quantity in the same regression.

Table A1. Regressions investigating the relationship between TFP growth and the change in the log of cellular licensed IoT connections per inhabitant and the log of mobile broadband connections per inhabitant.

	Dependent variable: TFP growth (ΔlnTFP)			
	First differences	First differences	Three years differences	Three years differences
ΔLog of Licensed IoT connections per inhabitant (ΔlnIoTpop)	0.03** (0.010)	0.02** (0.009)	0.04** (0.015)	0.03** (0.015)
ΔLog of mobile broadband connections per inhabitant (ΔlnMBBpop)		0.009* (0.005)		0.01 (0.007)
ΔLog labor quantity (ΔlnLQUANT)	–0.13 (0.080)	–0.13 (0.080)	–0.10 (0.116)	–0.10 (0.117)
ΔLog capital services (ΔlnK)	–0.13** (0.059)	–0.15** (0.059)	–0.14** (0.063)	–0.15** (0.065)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.15	0.16	0.19	0.20
Number of observations	574	574	410	410

Notes: Cluster robust standard errors are presented in parenthesis. ***, **, *indicate statistical significance at the 1%, 5% and 10% levels, respectively. Countries with extreme outliers for the dependent variable were removed from the sample. Labor quantity is generally based on total hours worked whenever available. Otherwise it is based on persons engaged.

Table A2. Regressions investigating the relationship between TFP growth and the change in the log of cellular licensed IoT connections per inhabitant and the log of mobile broadband connections per inhabitant

	First differences	First differences	Three years differences	Three years differences
	Dependent variable: TFP growth ($\Delta\ln TFP$)			
ΔLog of Licensed IoT connections per inhabitant ($\Delta lnIoTpop$)	0.03*** (0.010)	0.02** (0.009)	0.04*** (0.014)	0.03** (0.014)
ΔLog of mobile broadband connections per inhabitant ($\Delta lnMBBpop$)		0.01* (0.005)		0.01 (0.007)
ΔLog labor quantity ($\Delta lnLQUANT$)	−0.15** (0.076)	−0.16** (0.077)	−0.12 (0.114)	−0.13 (0.115)
ΔLog labor quality ($\Delta lnLQUAL$)	−0.58*** (0.143)	−0.60*** (0.143)	−0.77*** (0.212)	−0.80*** (0.212)
ΔLog capital services (ΔlnK)	−0.11* (0.057)	−0.12** (0.057)	−0.10* (0.060)	−0.12* (0.061)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.22	0.23	0.27	0.28
Number of observations	574	574	410	410

Notes: Cluster robust standard errors are presented in parenthesis. ***, **, *indicate statistical significance at the 1%, 5% and 10% levels, respectively. Countries with extreme outliers for the dependent variable were removed from the sample. Labor quantity is generally based on total hours worked whenever available. Otherwise it is based on persons engaged.

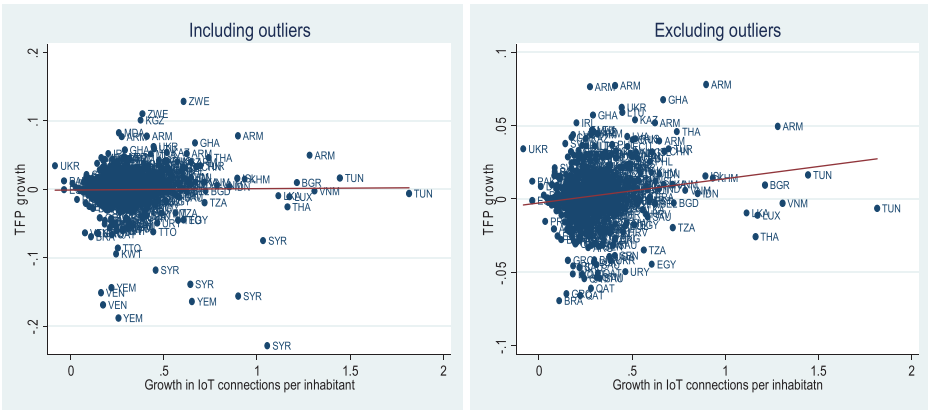## C: graphs with and without extreme outliers

Figure A1. Graphs of TFP growth and IoT connections per inhabitant with and without extreme outliers

D: robustness

D1: using robust regression techniques

Table A3 shows that our results remain robust when the rreg command is used to estimate our regressions. Moreover, the significance of the estimated variables is generally more significant once the rreg command is used in estimation.

Table A3. Regressions investigating the relationship between TFP growth and the change in the log of cellular licensed IoT connections per inhabitant and the log of mobile broadband connections per inhabitant based on the Cook distance outlier detector

	Dependent variable: TFP growth ($\Delta\ln TFP$)			
	First differences	First differences	Three years differences	Three years differences
ΔLog of Licensed IoT connections per inhabitant ($\Delta\ln IoTpop$)	0.03*** (0.004)	0.02*** (0.004)	0.04*** (0.005)	0.03*** (0.005)
ΔLog of mobile broadband connections per inhabitant ($\Delta\ln MBBpop$)		0.01*** (0.003)		0.01*** (0.004)
ΔLog labor services ($\Delta\ln QL$)	−0.25*** (0.029)	−0.27*** (0.029)	−0.11*** (0.036)	−0.15*** (0.037)
ΔLog capital services ($\Delta\ln K$)	−0.11*** (0.025)	−0.13*** (0.025)	−0.13*** (0.027)	−0.15*** (0.027)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.24	0.28	0.21	0.24
Number of observations	630	630	450	450

Notes: ***, **, *indicate statistical significance at the 1%, 5% and 10% levels, respectively. The rreg command in Stata was used to run regressions in order to control for extreme outliers.
The stata program rreg performs one version of robust regression of dependent and independent variables. It first performs an initial screening based on Cook distance >1 and remove outliers. It then performs Huber iterations and biweight iterations. For a more detailed description see Hamilton (1991). Tables A3 and A4 show the results based on the rreg result for the total sample and OECD and non-OECD countries respectively.

Table A4. Regressions investigating the relationship between TFP growth and the change in cellular licensed IoT connections per inhabitant and mobile broadband connections per inhabitant

	Dependent variable: TFP growth ($\Delta\ln TFP$)			
	OECD	OECD	Non-OECD	Non-OECD
ΔLog of Licensed IoT connections per inhabitant ($\Delta\ln IoTpop$)	0.02*** (0.006)	0.02*** (0.006)	0.02*** (0.007)	0.02*** (0.007)
ΔLog of mobile broadband connections per inhabitant ($\Delta\ln MBBpop$)		0.01 (0.009)		0.01*** (0.004)
ΔLog labor services ($\Delta\ln QL$)	0.004 (0.051)	−0.01 (0.052)	−0.31*** (0.040)	−0.32*** (0.040)
ΔLog capital services ($\Delta\ln K$)	−0.01 (0.043)	−0.02 (0.044)	−0.15*** (0.036)	−0.15*** (0.036)
Year dummies	Yes	Yes	Yes	Yes
R^2	0.14	0.14	0.27	0.30
Number of observations	252	252	378	378

Notes: ***, **, *indicate statistical significance at the 1%, 5% and 10% levels, respectively. The rreg command in Stata was used to run regressions in order to control for extreme outliers.

Table A4 shows that our results remain robust when the rreg command is used for OECD and non-OECD countries, respectively. Generally, the estimated coefficients of capital and labor services are negatively significant for non-OECD countries, while they are insignificant for OECD-countries. Finally, *Figure A2* shows TFP growth and labor services growth for OECD and non-OECD countries.*Table A4* shows that our results remain robust when the rreg command is used for OECD and non-OECD countries, respectively. Generally, the estimated coefficients of capital and labor services are negatively significant for non-OECD countries, while they are insignificant for OECD-countries. Finally, *Figure A2* shows TFP growth and labor services growth for OECD and non-OECD countries.

D2: Explorations using level regressions

Fixed effects can be accounted for by both within-group estimations and first differences. Within-group estimation implies that the mean values of the variables of the observations within a country are calculated and subtracted from the data of that specific country, which removes the unobserved effect. Thus, the model explains the variation around the mean of the dependent variable in terms of the variation around the means of the explanatory variables for the group of observations within a given country. An alternative approach is to use first differences which implies differencing each variable with adjacent periods. This eliminates the fixed effects as well as time-invariant regressors.

Based on data over two years (T = 2) within group estimation and first differences produce identical estimates and test statistics. When more than two years (T ≥ 3) are analyzed the two methods do not yield the same results, but they are both unbiased estimators under the underlying coefficient vector. However, when there is no serial correlation
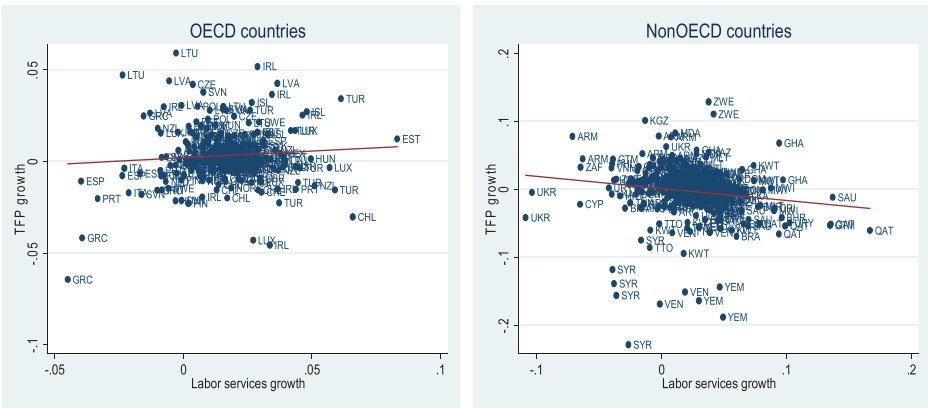
Figure A2. Graphs of first differences of TFP and labor services in OECD and non-OECD countries

of the idiosyncratic errors, within group estimation is most efficient. If the error terms follow a random walk process, i.e. there is substantial positive serial correlation, then first differencing is more efficient (Wooldridge 2009).

If the number of time-periods is larger than the number of countries (T > N) and if there is a unit root in any of the explanatory variables i.e. the variable is non-stationary, within group estimation is likely to generate a spurious regression. Thus, it is more appropriate to use first differences if any of the explanatory variables are non-stationary. However, if the number of time-periods (T) are very large, first differences are more sensitive to violations of the strict exogeneity assumption.

In general, a good rule would be to always include estimators based on within group estimation and first differences. Thus, it makes sense to report both sets of results and try to determine why they differ (Wooldridge 2009). Based on fixed effects estimation we find a strong significant association between TFP and licensed cellular IoT connections per inhabitant. Moreover, the coefficient remains significant at the one percent level when we control for mobile broadband connections per inhabitant, hours worked and capital estimates. Thus, our results are consistent with the findings based on first differences.[38]

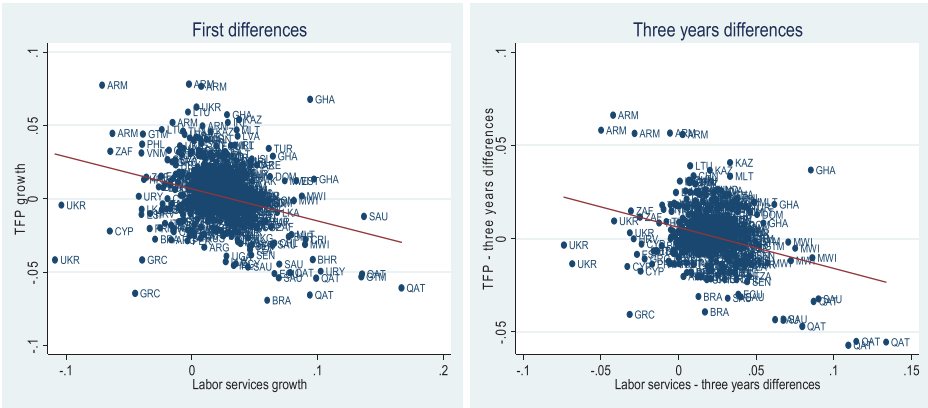## E: Graphs of first and three-year difference of TFP and labor services

Figure A3. Graphs of first and three-year differences of TFP and labor services

F: data appendix

Our analysis is conducted using two different datasets constructed from numerous sources. The econometric analysis is conducted using a dataset that includes data on TFP growth, factor input (labor and capital) services from the Conference Board Total Economy Database (TED) and supplemented with data on mobile broadband connections, cellular IoT connections and population estimates from the GSMA Wireless Intelligence Database. The data cover 82 countries, of which 36 are OECD members.

Our growth-accounting analysis relies on estimates of IoT investment from IDC and sales data from Ericsson annual report in 2018. Data on communications equipment prices, real CT and ICT investment growth, gross-value added, depreciation rates for CT equipment the net rate of return to capital are from the sources of growth dataset constructed by Goodridge, Haskel, and Edquist (2019). That dataset was constructed using national accounts data for 14 OECD countries (US and 13 EU countries) downloaded from OECD.Stat. Derived growth-accounting estimates were constructed using harmonized (with the US) ICT deflators and using the ex-post method such that the return to capital exactly exhausts gross operating surplus. For full details on the dataset and its construction, see Goodridge, Haskel, and Edquist (2019).

Estimates of global GDP used in both analyses are from the World Bank Development Indicators Database.

G: sources of growth data

Table A5 presents data on investment in CT equipment and broader ICT capital and their factor contributions. The top panel are snapshots of the share of CT (P_iI^{CT}) and ICT (P_iI^{ICT}) investment in total investment (ΣP_iI) and value-added (P_VV). The lower panels are averages, by period, of growth in real investment (ΔlnI) for CT and ICT equipment, the factor income share (sK), changes in capital services (ΔlnK) and factor contributions (ConΔlnK). Data are presented for both the US and EU-13.

From Table A5, we see that, as a share of total investment and value-added, investment in CT equipment and broader ICT capital was considerably higher in the US than the EU-13. On an approximate average basis, US CT investment was around double that in the EU-13, and US investment in broader ICT capital was around 50% higher than in the EU-13.

Moving to the lower panels, a similar pattern is observed for factor income shares and growth rates in real investment, capital services and factor contributions. Growth in real investment in CT equipment peaked in the late 1990s at 17% in the US and 12% in the EU-13. In that period, the contribution of CT equipment in the US stood at 0.19% as compared to 0.05% pa in the EU-13. Comparable growth rates for broader ICT capital in the investment boom of the late 1990s are 21% for the US and 16% for the EU-13, while the total ICT contribution peaked in the US at almost 1% pa, approximately double that observed in the EU-13.

We use these observed growth rates for real investment in CT and ICT capital to simulate growth in IoT capital services and the IoT contribution in the analysis of this paper.

Table A5. Sources of growth data: US and EU-13

	$P_iI^{CT}/\Sigma P_iI$	$P_iI^{CT}/\Sigma P_iI$	P_iI^{CT}/P_VV	P_iI^{CT}/P_VV	$P_iI^{ICT}/\Sigma P_iI$	$P_iI^{ICT}/\Sigma P_iI$	P_iI^{ICT}/P_VV	P_iI^{ICT}/P_VV
Year	US	EU-13	US	EU-13	US	EU-13	US	EU-13
1981	4.4%		0.9%		9.9%		2.1%	
1985	4.7%		0.9%		13.2%		2.6%	
1990	4.7%		0.8%		15.4%		2.7%	
1995	5.2%	2.7%	0.9%	0.5%	18.6%	13.3%	3.2%	2.2%
2000	6.8%	2.8%	1.3%	0.5%	24.4%	15.6%	4.6%	2.9%
2005	4.3%	2.1%	0.7%	0.4%	20.1%	14.5%	3.5%	2.5%
2010	4.1%	2.1%	0.7%	0.3%	20.6%	15.2%	3.4%	2.4%
2013	3.8%	2.0%	0.7%	0.3%	19.5%	16.0%	3.3%	2.5%
	mean ΔlnI^{CT} pa		mean sK^{CT}		mean ΔlnK^{CT} pa		mean $Con\Delta lnK^{CT}$ pa	
Period	US	EU-13	US	EU-13	US	EU-13	US	EU-13
	4.0%		1.8%		4.4%		0.06%	
1991–1995	7.6%		1.7%		4.6%		0.08%	
1996–1900	16.9%	11.9%	1.8%	0.8%	10.8%	6.6%	0.19%	0.05%
2001–2007	3.4%	4.9%	1.7%	0.7%	7.0%	5.9%	0.12%	0.04%
2008–2013	2.2%	3.9%	1.3%	0.5%	4.7%	5.3%	0.06%	0.03%
	mean ΔlnI^{ICT} pa		mean sK^{ICT}		mean ΔlnK^{ICT} pa		mean $Con\Delta lnK^{ICT}$ pa	
	US	EU-13	US	EU-13	US	EU-13	US	EU-13
1986–1990	9.9%		4.0%		9.0%		0.36%	
1991–1995	12.5%		4.5%		10.6%		0.48%	
1996–1900	20.6%	15.9%	5.6%	3.4%	17.9%	13.4%	0.98%	0.45%
2001–2007	5.1%	7.0%	5.9%	3.5%	7.5%	8.4%	0.45%	0.30%
2008–2013	2.8%	3.3%	5.2%	3.3%	4.2%	4.5%	0.22%	0.15%

Source: authors elaborations of data described in Goodridge, Haskel, and Edquist (2019). Note: Top panel are estimates of the share of CT and IT investment in total investment and value-added in selected years. Lower panels are mean values for the CT and ICT income share and growth rates in real investment, capital services and factor contributions for the periods shown. Growth rates estimated as the change in the natural log.