Baumol's Cost Disease in the Second Machine Age

Computerization, Productivity Growth and Employment 1998-2015

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Abstract

Baumol argued that technologically stagnant sectors with relatively low productivity growth over time will experience relatively higher prices and increased shares of total labor, and thereby slow aggregate growth. This theory, known as 'the cost disease', also claims that services, predominantly found in the public sector, generally are stagnant due to their perceived dependence on human labor as an input. In addition, computerization has been called 'the second machine age' since it is believed to change society and increase productivity on the same scale as industrialization once did. By combining these notions this thesis examines the relation between ICT, productivity growth and share of work hour development on sector level with EU KLEMS data for six advanced economies 1998-2015. This data supports Baumol's theory, though the explanatory capacity of the independent variables appears to be rather small. Moreover, the reliability of the study is questioned due to uncertainties in public sector productivity growth and doubts regarding ICT capital intensity quality as an ICT indicator. However, both computerization theorists and Baumol claims that GDP is an inadequate measurement tool for their purposes since it underestimates the effects of computerization and unbalanced growth, thus the real economic impact might be substantially larger than this study implies. In addition, a literature survey on labor economic theories on the computerization of the labor market is supplied to explain the historical development and, possibly, give some guidance of what the future holds.

Key words: *unbalanced growth, computerization, digitization, employment*

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1. Introduction

Computers have doubled their performance every 18 months for half a century, they have defeated the human champions in *Jeopardy!*, and they have learned how to drive cars (Brynjolfsson and McAfee, 2014). Contemporary human progress has been less impressive, especially in some areas: a string quartet still takes the same time to perform a Mozart concert today as when it was written. Since the leverage of technological advances have increased the market price for human labor over time, economic activities that have not decreased their labor input have become relatively more expensive (Baumol, 2011). In itself, this is not a problem: listening to music on Spotify has many advantages, especially from a cost perspective. However, it appears as the quality of many services – such as health care and education – is directly dependent on human labor as input, and thus are expected to become increasingly expensive over time. Indeed, they have increased their share of GDP over the past decades (ibid.).

This thesis intends to examine these notions by modestly addressing the following questions:

1) What are the characteristics of digital technologies?
2) Which tasks can be computerized?
3) What are the effects of computerization on labor productivity, employment, and the public sector?

The first step in this project is to observe a definition problem: "[t]he existing literature usually resorts to enumerations such as computer hardware, software and networks, descriptions like computer-based technology, computer-controlled equipment, information technology (IT), or simply other synonyms such as computerization and automation" (Bührer and Hagist, 2017, p. 116). To treat the references correctly, this tradition will be followed and terms describing economic activities related to Information and Communication Technology (ICT) will depend on context. In general, they will be referred to as *computerization*.

The second step is to recognize the significant amounts of research already devoted to this topic. Thus, a majority of this thesis consists of a *literature survey*, which is complemented by a *minor study* examining the sectoral computerization, productivity growth and work hour development in six advances economies in 1998-2015.

The literature survey is divided into three parts. The main topic of the first part is *digital technologies*, its effects on productivity and related measurement problems, all strongly influenced by Brynjolfsson and McAfee's book *The Second Machine Age* (2014).[1]

The second part concerns *computerization of modern work* and presents the most influencing theories on this topic: for example, Autor, Levy and Murnane's (2003) work on how computers have both replaced and complemented humans in the workplace and Frey & Osborne's (2013) method of determining different jobs' susceptibility to computerization, along with their prognosis for the upcoming two decades.[2]

The third part is dedicated to examine *Baumol's cost disease* (2012).[3] This theory claims that the relative cost of some economic activities, e.g. personal services, are bound to increase over time since their productivity growth is lower compared to other activities, e.g. manufactured products (Baumol, 1967, p. 415). The reason for its sick name is that "[i]f their relative outputs are maintained, an ever increasing proportion of the labor force must be channeled into these activities and the rate of growth of the economy must be slowed correspondingly" (ibid., p. 420). Furthermore, economic activities less susceptible to productivity growth are predominantly found within the public economy "which seems to leave policymakers with a trilemma; increase taxes (and hence tax distortions), cut spending or redistribute less" (Andersen and Kreiner, 2017, p. 417).

From this literature survey four hypotheses emerged:

1) *The Computerization Hypothesis*: Computerization leads to productivity growth.
2) *The First Cost Disease Hypothesis*: Productivity growth leads to fewer jobs.
3) *The Second Cost Disease Hypothesis:* Productivity growth is less prevalent within the public sector.
4) *The Combined Hypothesis:* Computerization leads to higher productivity growth and fewer jobs. Public sectors will have less productivity growth and more jobs.

To test these hypotheses, data from *EU KLEMS* (Jäger, 2017) for six advanced economies was utilized to identify national-independent sectoral trends between 1998-2015. In the study, the public sectors were represented by 'Public administration and defense; compulsory social

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[1] *The Second Machine Age* (Brynjolfsson and McAfee, 2014) will henceforth be referred to as 'SMA'.

[2] Autor, Levy and Murnane (2003) will henceforth be referred to as 'ALM'.

[3] *The Cost Disease* (Baumol, 2011) will henceforth be referred to as 'CD'.

security' (O), 'Education' (P) and 'Health and social work' (Q). Furthermore, the following variables were used to test the hypotheses:

- Computerization by ICT capital intensity in 2014, k_{ICT}
- Productivity growth by average GDP growth per work hour 1998-2015, g
- Fewer jobs by development in share of the total economy's work hours 1998-2015, ΔH

In addition, the selection of countries was semi-arbitrary, with the underlying idea to give some representation to Esping-Andersen's (1990) division of welfare regimes:

- *Liberal*: Market-oriented, guarantees only a minimum of social insurance while including private welfare schemes. Represented by US and UK.
- *Conservative*: Family-oriented, with social insurances excluding non-working wives while family benefits promote motherhood. The state only interferes when a family's capacity is exhausted. Represented by France and Italy.
- *Social-democratic*: Individual-oriented, with a universalistic system promoting equality of high standards, e.g. by socializing costs of welfare services. Represented by Denmark and Sweden.

It was shown that this division did not appear to play a highly significant role when it came to sector employment or national ICT intensity, although e.g. Denmark and Sweden had slightly higher employment in the education sector and significantly higher in the health sector.

The study supported all of the hypotheses by confirming that ICT capital intensive sectors in 2014 had a higher productivity growth 1998-2015 and a lower share of work hours in 2015 compared to 1998. In addition to this, the study confirmed that the public sectors O, P and Q, should be considered as (at least historically) stagnant sectors, since they experienced a relatively low productivity growth while increasing their share in work hours over the studied period. However, the highest obtained adjusted R^2 was 0.21, which indicates that the explaining variables – e.g. ICT capital intensity and productivity growth – in general have a small influence on the employment development for the time period in question. This small influence should however be put in perspective: both computerization theorists and Baumol believes that GDP's representation of cost reductions underestimates the effects on the real economy. Furthermore, doubts were raised regarding the accuracy of the growth data for the public sectors and the correctness of ICT capital intensity in 2014 as an indicator of computerization. In conclusion, though supporting the hypotheses, the results from the study should not be considered conclusive.

The remainder of this thesis is structured as follows: section 2 presents the literature survey. Section 3 presents the data source, EU KLEMS, and section 4 the method used in the study. Section 5 presents and analyzes the results from the study. Section 6 discusses the literature survey and the results from the study, and it identifies further work. Finally, section 7 summarizes the thesis.

2. Background

The intention with this literature survey is to adequately prepare the reader for the upcoming discussion on sectoral ICT intensity, labor productivity and employment development. Therefore, an overview of digital technology, computerization of the labor market and Baumol's cost disease is presented in named order.

2.1 Digital Technologies

> "Now comes the second machine age. Computers and other digital advances are doing for mental power – the ability to use our brains to understand and shape our environments – what the steam engine and its descendants did for muscle power. They're allowing us to blow past previous limitations and taking us into new territory." (SMA, pp. 7-8)

To be precise, *digitization* could be defined as "the work of turning all kinds of information and media – test, sounds, photos, videos, data from instruments and sensors and so on – into the ones and zeroes that are the native language of computers and their kin" (SMA, p. 61). However, it is the distinguishing features of digital goods that are most interesting from an economic perspective: they are *non-rival* and have a *marginal cost of reproduction close to zero* (SMA, p. 62). It is tempting to say that "[digital] information is costly to produce, but cheap to reproduce" (Shapiro and Varian, cited in SMA, p. 63), although the truth of this claim is questionable: today, exceptionally large amounts of information are generated for 'free' by user-generated sites, such as Facebook, and machine-to-machine communication (SMA, pp. 64-66).

GPT are technologies that "transform both household life and the ways in which firms conduct business" (Jovanovic and Rousseau, 2005, p. 1184). To qualify as a GPT, a technology should have the following characteristics:

1. *Pervasiveness* – The GPT should spread to most sectors.

2. *Improvement* – The GPT should get better over time and, hence, should keep lowering the costs of its users.

3. *Innovation spawning* – The GPT should make it easier to invent and produce new products or processes. (Jovanovic and Rousseau, 2005, p. 1185, emphasis in original)

Since ICT a) is used in almost every industry in the world, b) has improved performance exponentially while production costs have decreased and c) have led to innovations such as autonomous cars, it appears legitimate to classify ICT as a GPT, together with technologies such as the steam engine and electricity (SMA, p. 76).

It has been shown that productivity growth 1995-2007 increased significantly more in industries using IT extensively than other industries (Jorgenson, Ho and Samuels, 2011, p. 167). This claim will be tested later on in the study by:

The Computerization Hypothesis: Computerization leads to productivity growth.

However, as a GPT needs complements to reach its full potential, it takes time before any effects in labor productivity can be seen. A comparison between the productivity growth in the IT era and the introduction of electricity can be found in Figure 1, symbolizing the delayed productivity effects of earlier GPT's. In addition, productivity effects of IT are hard to measure; an early attempt to link IT investments to productivity increases can be seen in Figure 2.

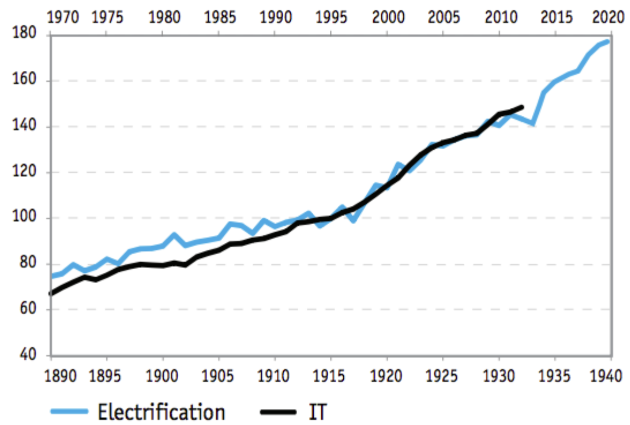

Figure 1. Labor productivity growth during the electrification era (bottom scale, 1915=100) and the IT era (top scale, 1995 = 100). Taken from Syverson (2013, p. 38)

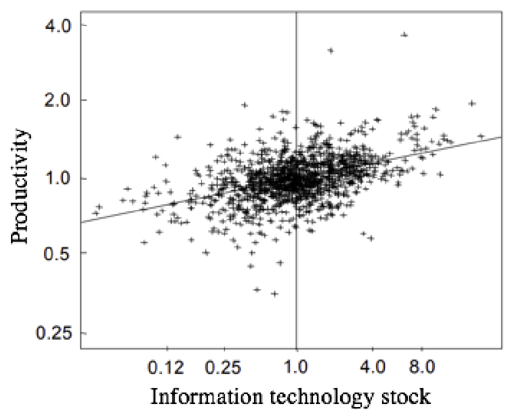

Figure 2. Productivity and information technology stock (capital plus capitalized labor), relative industry average, for large firms 1988-1992. Taken from Brynjolfsson and Hitt (2000, p. 32).

The early lack of productivity growth that could be attributed to IT was summarized by Robert Solow in 1987: "we see the computer age everywhere except in the productivity statistics" (quoted in Brynjolfsson and Hitt, 1998, p. 4). The notion that computing power per white collar worker had increased dramatically in the service sector since the 1970's without any traces of productivity increases became known as *the productivity paradox* (ibid., p. 3). This has been proven wrong since then, but it has been shown that it takes an average of 5-7 years from when the investments are made until all the benefits from them are visible in a firm's productivity numbers (SMA, pp. 104-105). It is believed that this delay is due to that complementary investments are needed to profit from IT: for every dollar invested in computer hardware, another nine dollars in software, training, and business process redesign were needed (SMA, p. 105). Some of these complementary investments, e.g. business processes, are a type of *intangible assets*, which unlike hardware and software generally are not accounted for as capital (SMA, pp. 120-121).

However, the measurement problem might to a greater extent depend on the use of GDP as a measurement standard. For example, free services like Wikipedia claims to have over fifty times the information of *Encyclopedia Britannica*, however, due to their non-existent prices, the value is not included in GDP accounting (SMA, p. 111). In effect, since we might prefer Wikipedia both for economic and qualitative reasons, digitization could actually have a *negative effect* on GDP; thus, we should avoid mixing up *GDP growth* and *economic growth* (SMA, p. 111).

A better way to estimate the benefits from digitization could be by *economic surplus*: the difference between how much a consumer would have been willing to pay for something compared to what they actually paid (SMA, p. 114-115). However, such data is difficult to get hold off. One way the benefits of internet has been estimated is by observing how much *time* people spent on it; e.g., Americans almost doubled the amount of time they spent on the internet 2000-2011, implying that they preferred this over other activities. By attributing a dollar value to this time, it was estimated that internet created $2600 of value per user and year in 2012. Of course, none of this was included in the GDP statistics, though if it had been, US productivity growth would have been 1.5% instead of 1.2% in 2012. In addition, ICT has generated an abundance of new goods and services – e.g. Spotify, Wikipedia – which by their pure existence increases consumer surplus, even though we do not quantify this in GDP measurements (SMA, p. 117). In conclusion, "the rise in digital business innovation means we need innovation in our economics metrics" (SMA, p. 122).

To summarize, ICT should be considered as a GPT and digital goods differ from normal goods by being *non-rival* and have a *marginal reproduction cost close to zero*. Moreover, a hypothesis was formulated claiming that increased ICT capital intensity leads to productivity growth. Finally, it was argued that any GDP measurements of ICT productivity effects based on ICT capital will presumably miss the costs of complementary investments, but also underestimate the unmeasured economical gains.

2.2 Computerization of Modern Work

> "Technological progress is going to leave behind some people, perhaps even a lot of people, as it races ahead. As we'll demonstrate, there's never been a better time to be a worker with special skills or the right education, because these people can use technology to create and capture value. However, there's never been a worse time to be a worker with only 'ordinary' skills and abilities to offer, because computers, robots, and other digital technologies are acquiring these skills and abilities at an extraordinary rate." (SMA, p. 11)

The development of men's wages in the US sorted by educational level for the years 1963-2008 can be found in Figure 3. As can be seen, the more educated groups had a more favorable wage development than the less educated, especially since the 1980s. It could also be noted that the real-wages of the least educated group was lower in 2009 than it was in 1963, indicating that the benefits from computerization have not been distributed equally.

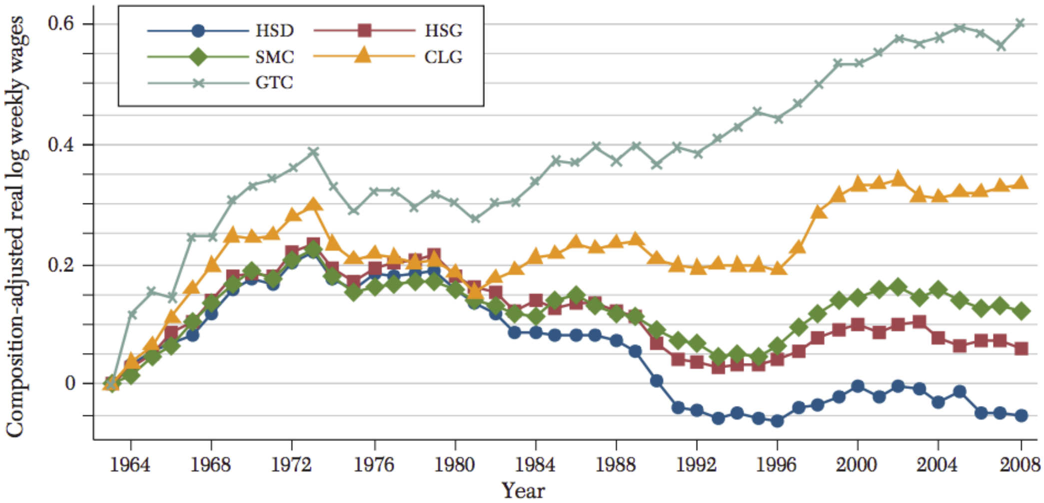

Figure 3. Development of men's wages in US 1963-2008: High-school drop-out (HSD), High-school graduate (HSG), some college (SMC), college graduate (CLG) and greater than college (GTC). Taken from Acemoglu and Autor (2012, p. 439).

A traditional way to model the labor market is to divide the workforce by their estimated skills, for example into high-skilled (e.g. college graduates) and low-skilled workers (e.g. high school graduates), and then use the log wage ratio between these groups as an indicator of the relative supply and demand for these skills. Acemoglu and Autor call this approach *the canonical model* (2012, pp. 433-435). This model assumes that the two skill groups have imperfectly substitutable occupations and that technology is *factor-augmented*, i.e. it increases the productivity for one of the groups (or both). Thereby the model is able to capture the empirical fact seen in Figure 3: technology appears to have rewarded high-skilled workers, so-called *skill-biased technical change* (SBTC). This development is sometimes described as "the race between education and technology" (Goldin and Katz, 2007). The mathematical expression for this model is:

$$\ln\omega = c + \frac{\sigma - 1}{\sigma}\ln\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma}\left(\frac{H}{L}\right) \qquad (2\text{-}1)$$

In Eq. (2-1), ω is the wage premium for high-skilled workers ($\frac{\omega_H}{\omega_L}$), c is a constant, σ is the elasticity of substitution between high-skill and low-skill labor, A_H and A_L are factor-augmenting technology terms for high-skilled and low-skilled workers, while H and L are the total supplies of high-skill and low-skill labor, respectively. Thus, the term A_H/A_L corresponds to the skill-bias of technology and H/L the relative supply of skills (Acemoglu and Autor, 2012, p. 434). The result of applying this model to US data can be found in Figure 4.

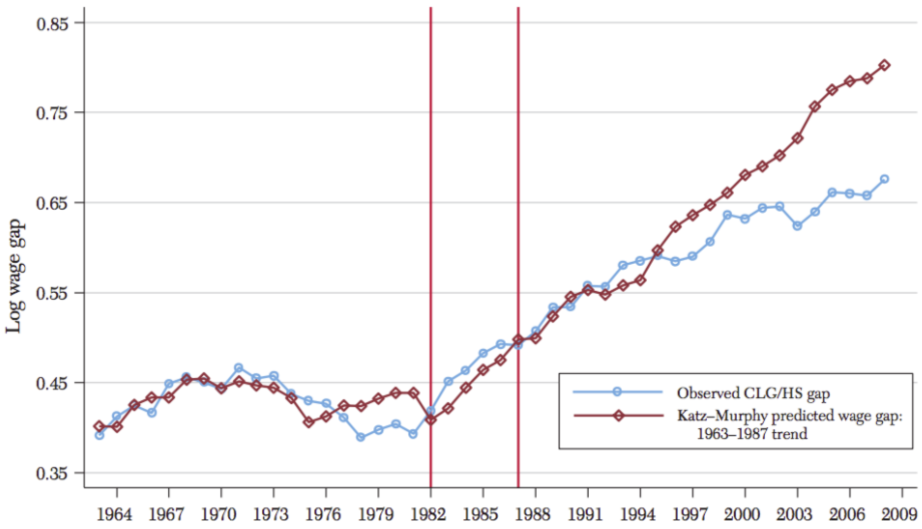

Figure 4. Applying the canonical model (red squares) to US data (blue circles) showing the wage premium of college education. Taken from Acemoglu and Autor (2012, p. 437).

In Figure 4, it appears as the model performs well until 2000, when it starts to diverge from reality. However, the model appears unable to explain some of the developments found in Figure 3. For example, the increasing wage gap from 1980 and onwards is a combination of increasing wages in the top and decreasing wages in the bottom; yet, the canonical model claims that a demand shift favoring skilled workers will not only raise the wage premium, but also boost the earnings of all skill groups (Acemoglu and Autor, 2012, p. 439). This is clearly not true. Furthermore, the fact that technologies in the canonical model are factor-augmenting means that there are no skill-replacing technologies (ibid., p. 434). This is a highly counterintuitive claim: e.g. most jobs within agriculture have been automated away over the years as well as phone operators and human computers. Finally, the canonical model appears to be unable to explain why the wages have stabilized for the lower educated groups since 1990.

Thus, even though the canonical model has been able to find correlations between e.g. the adoption of ICT and the increased demand of high-skilled labor, it "merely labels the correlation without explaining its cause. It fails to answer of what it is that computers do – or what it is that people do with computers – that causes educated workers to be relatively more in demand" (ALM, p. 1279-1280). Instead, ALM proposes a *routinization hypothesis*, where tasks are grouped in accordance with their relation to computerization, see Table 1.

Table 1. The division of work into tasks according to ALM (p. 86).

Task type	**Routine tasks**	**Nonroutine tasks**
	Analytic and interactive tasks	
Examples	• Record-keeping • Calculation • Repetitive customer service (e.g. bank teller)	• Forming/testing hypotheses • Medical diagnosis • Legal writing • Persuading/selling • Managing others
Computer impact	Substantial substitution	Strong complementarities
	Manual tasks	
Examples	• Picking or sorting • Repetitive assembling	• Janitorial services • Truck driving
Computer impact	Substantial substitution	Limited opportunities for substitution or complementarity

ALM's model can be described as *task-biased technological change* (TBTC), where computer capital can 1) substitute for workers in routine tasks and 2) complement workers in non-routine tasks (p. 1280). Here, 'routine' is defined as a task that can be accomplished by a machine if it follows programmable rules, and 'non-routine' if it cannot.

There are two concepts that should be noticed regarding routine tasks: first, *Polanyi's notion* of "[w]e can know more than we can tell" (Polanyi, cited in ALM, 2003, p. 1283); i.e. there are things we 'know' how to do, though we are still unable to explain how we do them to a machine. Second, *Moravec's paradox*: "high-level reasoning requires very little computation, but low-level sensorimotor skills require enormous computational resources" (Wikipedia, cited in SMA, pp. 28-29). In essence, computers are only better than humans at some specific tasks.

In this model, automation does not only *substitute* for labor, it also *complements* labor: for example, by increasing productivity, raising income and augmenting demand for labor (Autor, 2015, p. 5). Moreover, tasks that cannot be substituted will in general be complemented by it, increasing the value of that specific activity. This complementarity can be exemplified with the O-ring model, where the failure of any step in the production chain leads to process failure; thus, if the reliability of any of the other steps increases, then the value of succeeding in the remaining steps increases. Thereby, "when automation or computerization makes some steps in a work process more reliable, cheaper, or faster, this increases the value of the remaining human links in the production chain" (Autor, 2015, p. 6).

A strength with TBTC compared to SBTC is that it is able to capture the disproportionate growth of low- and high-income jobs compared to middle-income jobs over the last decades, known as *job polarization*, see Figure 5. In this figure, it can be seen that the employment share in middle-income jobs have disappeared throughout the advanced economies since the beginning on the 90's. In addition to this, *jobless recovery* is a term referring to the recent recessions in the digital era – 1991 , 2001, 2009 – where, after the crunch, "investments in equipment and software returned to pre-crisis levels, but middle-skill employment didn't" (Bührer and Hagist, 2017, p. 122).

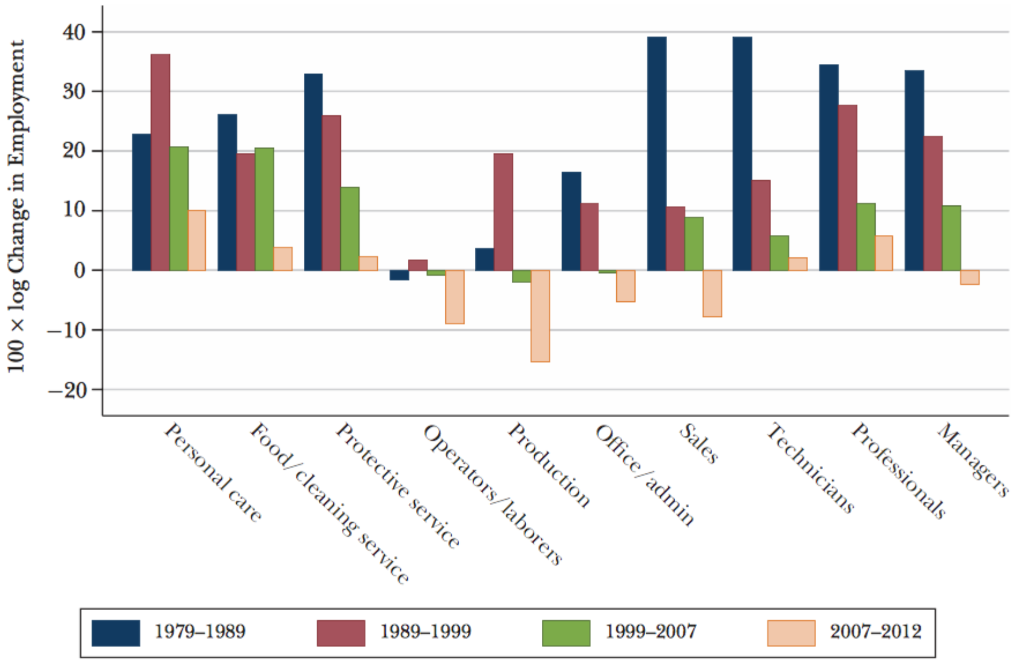

Figure 5. Change in employment by major occupational category ins US, 1979-2012. Low-income jobs are to the left, middle-income jobs in the middle and high-income jobs to the right (Autor, 2015, p. 13).

Autor argues that three main factors determine if a worker will benefit from a technological change (2015, p. 7):

1) If the technology mainly *complements or substitutes* their work tasks
2) How the technology affects final demand in regards of *income and substitution effects*
3) How the technology relates to *the elasticity of labor supply*, i.e. if an abundant supply of labor could complement the technology, substantial wage gains are unlikely

Looking at abstract task-intensive occupations, such as managers or physicians, they will be strongly complemented by ICT since it enables them to "further specialize in their area of comparative advantage, with less time spent on acquiring and crunching information and more time spent on interpreting and applying it" (Autor, 2015, p. 15). In addition, the demand for such services – e.g. health care – does not appear to decline, even though the output from such occupations has increased substantially by technological progress. Finally, labor supply to these occupations appears to be rather inelastic, since they demand college degrees which take years to obtain (and presumably demands some level of educational aptitude). Thus, even though the wage premium for education has increased substantially over time (see Figure 3), the labor supply has not nearly met the demand. In conclusion, workers in most abstract task-intensive occupations will benefit from a combination of strong complementarity, inelastic demand for their services and inelastic labor supply to their profession.

On the other end of the spectra, most manual task-intensive occupations, such as janitors or home health aides, rely little "on information or data processing for their core tasks, and involve only limited opportunities for either direct complementarity or substitution" (Autor, 2015, p. 16). Moreover, the final demand for such work is relatively price inelastic, thus productivity gains in such occupations do not affect customer prices. However, "demand for manual task-intensive work appears to be relatively *income* elastic" (ibid, p. 17, emphasis in original). Thus, when income increases, so does the demand for such services. An important difference between abstract and manual task-intensive occupations is that the latter has an intrinsically elastic labor supply, due to their low entry requirements. Thus, though ICT appears to have strongly contributed to *employment polarization*, it has not resulted in an equal *wage polarization* in favor of manual task-intensive work; possibly the labor supply also increased by workers displaced in other sectors of the economy (ibid., p. 18). The empirical data in Figure 6 supports this view, where the low-income jobs can be found to the left.

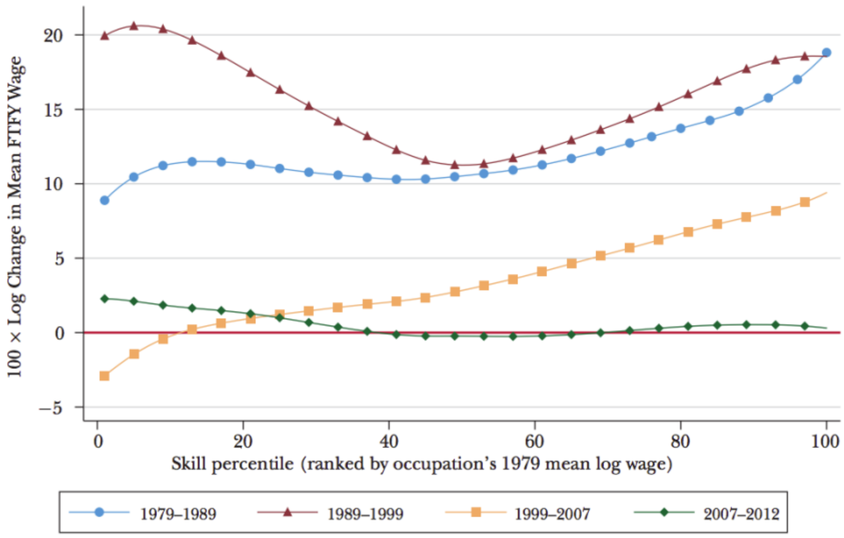

Figure 6. Changes in log mean wages for different skill percentiles in the US over four time periods, taken from Autor (2015, p. 18).

Here, it can be seen that even though there was a higher wage growth for low-skilled occupations in the 1990's than for middle-skilled occupations, this changed in the 2000's which does not correspond to the employment data for the same time period (which can be estimated from the trends in Figure 5). In general, it can be seen that there has been essentially no wage growth in the U.S. since 1999, with exception for high-skilled occupations.

Since 1999, there has been a downward trend also for high-skilled occupations, both in wage and employment. This is probably not due to technology substitution of abstract task-intensive occupations, because such a substitution should correlate with an increase in ICT investments which has not been identified (Autor, 2015, p. 21). Instead, the decline could possibly be attributed to a) *business cycles*, where the 'dot-com' bubble in 2000 and the financial crisis in 2007-2008 have kept down investments and innovations, and b) *globalization*, where e.g. China's manufacturing exports have decreased labor demand in import-competing industries (Autor, 2015, p. 22).

Yet, technology advances quickly and what was considered non-routine 15 years ago might not be so any more: "today, the problems of navigating a car and deciphering handwriting are sufficiently well understood that many related tasks can be specified in computer code and automated" (Frey and Osborne, 2013, p. 15). However, since it is difficult to accurately predict when certain technologies become available, Frey and Osborne utilized the inverse approach: first, they identified bottlenecks, i.e. activities believed to be very hard to substitute with technology – e.g. *finger dexterity, originality* and *social perceptiveness* – and then they assumed that everything else could be computerized within 20 years.[4] By mapping these bottlenecks to the American O*NET database, which describes the content of occupations, and linking these to the US Labor Department's Standard Occupational Data, Figure 7 emerged with an estimate of jobs that could be replaced by technology within the next 20 years.

[4] The full list of substitutable skills can be found in Appendix B.

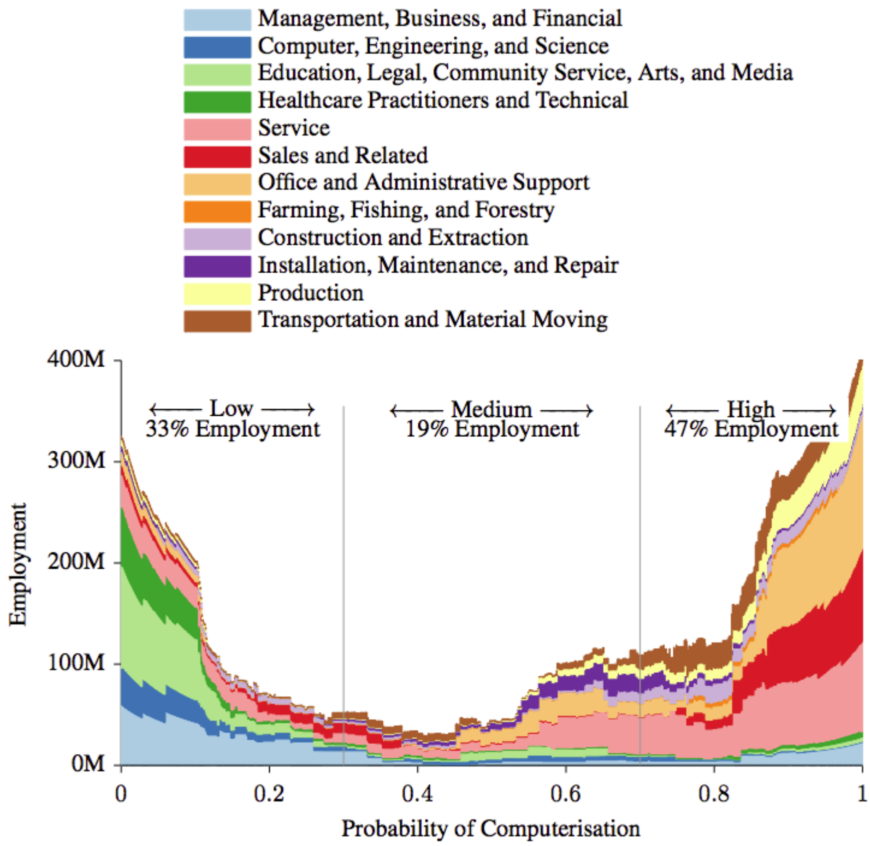

Figure 7. Distribution of BLS 2010 occupational employment and the probability of computerization. The total area under all curves is equal to total US employment (Frey and Osborne, 2013).

The results in Figure 7 should naturally be considered with caution, as these numbers are not the probability that jobs will disappear, but if they *could* be computerized. However, as can be seen, 47% of US jobs have a high probability of computerization, especially in the service, sales and office sectors. The probabilites within education, health care, science and management appear to be substantially lower. Notably, this would break the current trend and *mainly affect low-skill and low-wage occupations*. Thus, low-skill workers would have to reallocate to jobs that are not computerized, which according to Frey and Osborne's theory would consist of tasks requiring creative and social intelligence (2013, pp. 44-45).

In summary, the labor market in advanced economies have polarized over the past decades: middle-income jobs have disappeared, whereas new low-income and high-income jobs have been created. ALM's task-biased technological change model, dividing tasks into 'routine' and 'non-routine' depending on their replaceability by computers, appears to be capable to describe this development more accurately than earlier labor market models. However, ALM's definition of what is considered nonroutine is contingent on technological advances, and according to Frey and Osborne (2013) approximately 50% of current jobs are susceptible to computerization within two decades. The occupations believed to be least susceptible to computerization are those that are highly dependent on finger dexterity, originality and social perceptiveness. Finally, it appears as the ongoing computerization will continue the polarizing trend, however, it is believed that the coming advances in computerization will primarily increase the possibilities to replace low-income jobs.

2.3 Baumol's Cost Disease

> "Rising productivity clearly makes a nation wealthier and helps to contain poverty, but it also underlies the cost disease and the rising real costs of the affected services. A disturbing moral of the story is that the products most vulnerable to the cost disease include some of the most vital attributes of civilized communities: health care, education, the arts, police protection, and street cleaning, among others." (CD, p. 27)

The cost disease is derived from the notion that "*if the prices of all commodities are not rising at the same pace, then some must be increasing at a rate above average*" (CD, p. 19, emphasis in original). To clarify the concept, economic sectors producing commodities can be divided into two groups:

1) Technologically *progressive* sectors, e.g. manufacturing industries, where innovations, capital accumulation and large-scale economies cumulative permit large increases in productivity.
2) Technologically *stagnant* sectors, e.g. services in the form of health care, where the strong reliance on human services only permits small increases in productivity.

Provided that the progressive sector's productivity growth results in wage increases and labor can move freely between sectors, the same wage increases will appear also in the stagnant sector. However, while the manufactured products will not increase their prices due to productivity growth offsetting the wage increase, the price for the service has to rise in proportion to the wage increase. Baumol argues that these variations in productivity growth over time will result in substantial relative price increases in the stagnant sector "making personal services enormously more expensive than manufactured goods" (CD, p. 22).

Earlier empirical studies of Baumol's cost disease have confirmed that services in general have a lower productivity growth and that the prices of services grow faster (Nordhaus, 2008). Furthermore, structural changes where employment shares have decreased in the manufacturing sectors have been observed in all OECD countries (Andersen and Kreiner, 2017) and the costs of health care have increased for the past four decades in all advanced economies (CD, p. 12).

Originally, Baumol described the cost disease as *unbalanced growth* with the mathematical description that follows (1967, pp. 417–419).[5] First, output Y from two firms, one progressive (M = manufacturing) and one stagnant (S = service), can at time t be described as:

$$Y_M(t) = A_M L_M(t) \cdot e^{rt} \tag{2-2}$$

$$Y_S(t) = A_S L_S(t) \tag{2-3}$$

Here, L is the quantity of labor employed and A is the initial productivity, which in the progressive sector grows at a constant rate r.[6] Assuming wages W are equal in the two sectors and grow in accordance with the productivity of the progressive sector, the following is true:

$$W_M(t) = W_S(t) = W \cdot e^{rt} \tag{2-4}$$

The cost per unit of output C will then be:

$$C_M(t) = \frac{W_M(t)L_M(t)}{Y_M(t)} = \frac{W \cdot e^{rt} L_M(t)}{A_M L_M(t) \cdot e^{rt}} = \frac{W}{A_M} \tag{2-5}$$

$$C_S(t) = \frac{W_S(t)L_S(t)}{Y_S(t)} = \frac{W \cdot e^{rt} L_M(t)}{A_S L_S} = \frac{W \cdot e^{rt}}{A_s} \tag{2-6}$$

Over time, the relative costs will increase in accordance with:

$$\frac{C_S(t)}{C_M(t)} = \frac{L_S(t)/Y_S(t)}{L_M(t)/Y_M(t)} = \frac{A_M \cdot e^{rt}}{A_s} \tag{2-7}$$

In general, it is expected that the demand for S would decline. If we, for example, suppose that S and M has perfect demand elasticity, the output ratio would be given by:

$$\frac{Y_S(t)}{Y_M(t)} = \frac{A_S L_S(t)}{A_M L_M(t) \cdot e^{rt}} = \frac{K_{el}}{e^{rt}} \tag{2-8}$$

Here, K_{el} is a constant given by the original ratio between labor productivities and quantities. Thus, the output from a non-progressive sector with elastic demand would over time decline and, eventually, perish. However, if demand for the service is more inelastic – say health care – it might be reasonable to assume that the magnitude of the relative outputs is maintained:

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[5] Some notations are changed from Baumol's original description.

[6] In a more generic case, r corresponds to the relatively higher growth of the relatively more progressive sector.

$$\frac{A_M}{A_S}\frac{Y_S(t)}{Y_M(t)} = \frac{L_S(t)}{L_M(t) \cdot e^{rt}} = K_{inel} \tag{2-9}$$

If $L(t) = L_M(t) + L_S(t)$ is the total labor supply, then it follows from Eq. (2-9) that:

$$L_S(t) = \big(L(t) - L_S(t)\big)K_{inel} \cdot e^{rt} = \frac{L(t)K_{inel} \cdot e^{rt}}{(1 + K_{inel} \cdot e^{rt})} \tag{2-10}$$

$$L_M(t) = L(t) - L_S(t) = \frac{L}{(1 + K_{inel} \cdot e^{rt})} \tag{2-11}$$

In this case, when t approaches infinity, L_S will approach L whereas L_M will approach zero. In other words, more and more of the labor will be transferred to the stagnant sector and growth will approach zero, provided that the ratio of the outputs is held constant and L does not increase. From this argument, the second hypothesis to be tested in the study is derived:

The First Cost Disease Hypothesis: Productivity growth leads to fewer jobs

Some clarifications to Baumol's theory might be needed. He writes that "*productivity growth* is defined as a labor-saving change in a production process so that the output supplied by an hour of labor increases" (CD, p. xx, emphasis added). In addition, *services* are a broad and diverse economic activity, e.g. the growth performance of businesses services such as ICT should not be mixed up with the more stagnant consumer services, since the former is used as *inputs* to other commodities and, almost by definition, generates productivity improvements (CD, p. 123). Furthermore, Baumol claims that there are "two reasons that growth has eluded the stagnant services" (CD, p. 22). First, services appear to have an inherent resistance to standardization, which can be exemplified by the difference between producing identical cars and repairing them. Second, it is common that the quality of a service is – at least believed to be – inherently correlated to the amount of human labor invested in the production. For example, we might believe that speeding up the work of teachers will result in students learning less. Baumol thinks that this belief is partly incorrect as it could be the result of self-deception by providers and customers: e.g., it is plausible that filmed lectures by an outstanding teacher shown to thousands of students may provide better learning opportunities than a traditional classroom, and "recorded music is sometimes even preferable to live performance" (CD, p. 23). However, even though there is room for improvements within the service sector, this is not an objection to the general concept: progressive sectors will achieve higher growth rates, and the costs for commodities from the stagnant sectors will increase as a result of this.

One might object that it appears as the benefit associated with productivity growth has escaped Baumol: if we are able to produce good A cheaper than before, we still have the opportunity to consume just as much of good B and it is only the price relative to good A that has increased. In fact, we could consume even more of good B, since we need less input to produce the same amount of good B. Or, as Baumol puts it: "[i]f the amount that can be produced by an hour of labor increases for almost every commodity and decreases for none, then more of *everything* can be provided for the public to consume" (CD, p. 43). Thus, the cost disease "turns out to affect only the way in which we divide up the money we spend" (CD, p. 53), i.e. it is no different from normal consumption subjected to income and substitution effects.

However, Baumol claims that "it is inherent in the economic growth process that the economic activities for which labor-saving innovation is difficult to come by are often the very activities that are generally considered most critical for society's welfare" (CD, p. 27). If this is correct, there remains only two possibilities: either funding for those services must increase, by tax or private financing, or the quality must decline (CD, p. 61). This gives our third hypothesis:

> *The Second Cost Disease Hypothesis:* Productivity growth is less prevalent within the public sector

At this point, it is also possible to combine all the previous hypotheses into one:

> *The Combined Hypothesis:* Computerization leads to higher productivity growth and fewer jobs. Public sectors will have less productivity growth and more jobs.

Moving on, Baumol identifies the same problem as was discussed earlier on computerization: GDP is a problematic economic indicator.[7] He exemplifies this by claiming that the manufacturing sector's share of GDP has decreased due to a *fall in prices*, not in the *actual quantity* of manufacturing output (CD, p. 78). He further argues that we should use *quality-unadjusted* productivity measures, and that we need to recognize the difference between *quality-improving productivity growth* and *cost-saving productivity growth*, where the cost disease measures the latter type (CD, p. 83). This distinction is important, since we want to measure "how much money consumers must pay for a product, not how desirable that product is" (CD, p. 84). As an example, Baumol describes an innovation in cardiac surgery that doubles the cost, but trebles the life expectancy; surely, this is a significant qualitative improvement.

[7] He actually suggests another unit for measuring economic progress: "how many working hours it takes to acquire the income needed to buy the things we purchase" (CD, p. 48). I will not pursue this measure further in this thesis, though I believe my use of relative work hours as a parameter in the EU KLEMS study is a step in this direction.

However, if a patient only could afford the old method and it no longer is available, in what way does this innovation benefit him? Or if the hospital takes on the cost but has to keep its budget, where will it make the corresponding cuts? It appears as there are situations where quality improvements not necessary are Pareto improvements.

In summary, Baumol's cost disease predicts that some sectors will be *progressive* and experience higher productivity growth than *stagnant* sectors. As an effect, the relative price of stagnant sectors' output will increase over time and, in general, fewer will be employed in the progressive sectors. This has been empirically confirmed and will be tested once more in the study. Baumol further claimed that public sectors in general are more stagnant than market sectors, which also will be tested in the study. In addition, Baumol claimed that GDP will underestimate the real growth in progressive sectors due to cost reductions from their productivity increases. Finally, it was argued that even though the stagnant services' relative cost increase, the society is still richer as a whole; thus, by a redistribution of resources, the cost disease would be cured.

3. Data

This section presents the data source, EU KLEMS (Jäger, 2017), and is deliberately kept short while still providing the reader with a sufficient understanding of the variables' origin and content. Unless otherwise indicated, information is taken from O'Mahony & Timmer (2009), where the interested can find their method explained in more detail.

The *EU KLEMS Growth and Productivity Account* is a database which contains "industry-level measures of output, inputs and productivity for 25 European countries, Japan and the US for the period from 1970 onwards" (p. F374). The economy of each country is divided into 34 industries based on NACE Rev.2 / ISIC Rev. 4; this division can be found in Table 13 in Appendix A. The EU KLEMS growth accounting model is based on the production possibility frontier theory where the industry gross output (Y) is a function of capital (K), labor (L), intermediate inputs (X) and technology (the residual), indexed by time (t) and industry (j):

$$\mathrm{Y}_j = f_j(K_j, L_j, X_j, t) \tag{3-1}$$

Assuming competitive factor markets, full input utilization and constant returns to scale, output growth can be expressed with the cost-share weighted two-period average growth of inputs and technological change (A^Y) on a translog functional form:

$$\Delta \ln Y_{jt} = \bar{v}_{jt}^{K} \Delta \ln K_{jt} + \bar{v}_{jt}^{L} \Delta \ln L_{jt} + \bar{v}_{jt}^{X} \Delta \ln X_{jt} + \Delta \ln A_{JT}^{Y} \qquad (3\text{-}2)$$

where $\bar{v}_{jt}$ is the two-period average share of input i in nominal output, where:

$$v_{jt}^{K} = \frac{P_{jt}^{K} K_{jt}}{P_{jt}^{Y} Y_{jt}};\ v_{jt}^{L} = \frac{P_{jt}^{L} L_{jt}}{P_{jt}^{Y} Y_{jt}};\ v_{jt}^{X} = \frac{P_{jt}^{X} X_{jt}}{P_{jt}^{X} Y_{jt}} \qquad (3\text{-}3)$$

and $\bar{v}_{jt}^{K} + \bar{v}_{jt}^{L} + \bar{v}_{jt}^{X} = 1$. In Eq. (3-2), each element on the right-hand side indicates the proportion of output growth that is accounted for by capital services (K), labor services (L), intermediate inputs (X) and technical change (A^Y). The term A^Y is known as the Multifactor Productivity (MFP) or Total Factor Productivity (TFP), since this residual growth is assumed to measure the disembodied technological change. Capital growth is divided into ICT and non-ICT assets by the period-average weight share of ICT assets in total capital costs in the industry *j* at time *t*. A similar procedure is also applied to labor, where the growth is divided into hours worked (H) and changes in labor composition (LC), such as education, age and gender.

Moreover, ICT assets are considered to be computing equipment (IT), communication equipment (CT) and software, see Figure 15 in Appendix A. Capital is measured as capital services using the perpetual inventory method (PIM) with geometric depreciation profiles. The weights for the capital inputs are based on the rental price of each asset, consisting of a nominal rate of return, depreciation and capital gains. The nominal rate of return is the value for the capital services, which is derived as the gross value added minus the labor compensation. The depreciation rate for IT and software is 31.5% and for CT 11.5% (Jäger, 2017).

Following this procedure EU KLEMS provides the variables presented in Table 2, which are renamed in the thesis for convenience. The LP1 parameters measures value added per hour worked, which is preferred since the hypotheses need a measure of productivity increase, and as such it should be measured in output per work hour. These numbers are only available between 1998-2015 and thus limits the temporal scope of the thesis. However, this is presumably a good period, since it covers approximately two business cycles and are in similar positions in the business cycles. The Kq parameters measures real fixed capital stock (2010 prices), where 2014 is chosen since it is the latest year available for all countries.

Table 2. Overview of EU KLEMS variables used in the study together with the thesis variable name and description.

EU KLEMS variable	Thesis variable	Description
H_EMP	H	Total hours worked by persons engaged
Kq_GFCFC	k	All capital assets
Kq_IT	k_{IT}	Computer equipment
Kq_CT	k_{CT}	Communications equipment
Kq_Soft_DB	k_{SW}	Computer software and databases
LP1_Q	g	Growth per work hour
LP1ConLC	g_{LC}	Labor composition change contribution to growth
LP1ConKIT	g_{ICT}	ICT capital services contribution to growth
LP1ConKNIT	g_{NICT}	Non-ICT capital services contribution to growth
LP1ConTFP	g_{TFP}	Total Factor Productivity contribution to growth

As with all data, "there are some resolved measurement issues" (p. F390-F395). There is no need to go into detail of all of them as these can be found in O'Mahony and Timmer (2009), however it makes sense to highlight some relevant issues. One problem is that services measuring output is less reliable for services, since they are "intangible, more heterogenous than goods and often depend on the actions of the consumer as well as the producer" (p. F391). This is extra prominent within the public sector, i.e. public administration education, health and social services, where there is a lack of market prices: "productivity measures for these sectors should therefore be interpreted with care, if at all" (ibid., p. F391). However, they add that "EU KLEMS data may well be useful in considering the use of ICT or skilled labour in the health sector across countries" (ibid., F391).

Furthermore, the labor change composition is divided into three categories (high, medium and low) which can lead to biases and the same occupation can be classified different between countries. Moreover, in Sweden, it appears as re-classification also can be an issue, see Figure 8. Here, g_{LC} is around zero for most sectors – which is expected, since changes in labor composition are expected to be slow – with exception for O, P, Q and S, whom all are services (see Appendix A). Moreover, in the cases of O, P and Q they are offset by a highly negative g_{TFP}, thus, there appears to exist good reasons to doubt that this high g_{LC} (and the corresponding g_{TFP}) is correct for Sweden.

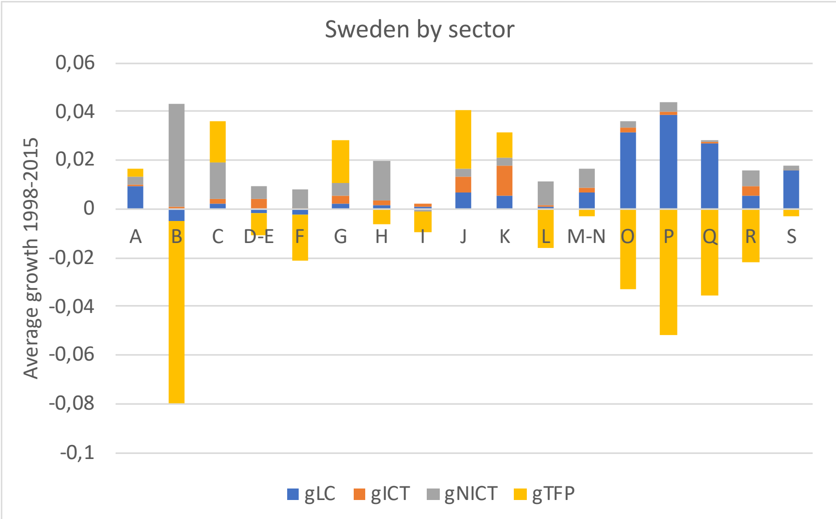

Figure 8. Average growth 1998-2015 for sectors A-S in Sweden attributed to labor composition (LC), ICT-capital (ICT), non-ICT capital (NICT) and TFP.

Regarding the depreciation rates, they are "held constant over time and across countries. Most likely these assumptions do not hold" (p. F393), but it is considered to be the best possible solution. Finally, TFP is sometimes negative (as seen in Figure 8) which is impossible under strict neo-classical assumptions; however, as a residual, this also includes the effect of unmeasured inputs and measurement errors in general.

In summary, the data used in the study comes from the EU KLEMS database. However, there are good reasons to be skeptical about the reliability of the data, especially for the public sector.

4. Method

In this section, an overview of the method used in the study is provided together with a description of the variable processing. For ease of reading, the approach for testing each specific hypothesis is presented in the 'Results' section together with the corresponding results.

4.1 Overview

The objective of the study is to test the four hypotheses on computerization and Baumol's cost disease. An overview for the test setup can be found in Table 3 and for the test variables in Table 4. In short, each hypothesis is first evaluated with a scatter plot of the relevant variables, outliers are identified and – if motivated – removed from the sample.

Table 3. Overview of the hypotheses' indicators and parameters.

Hypothesis	Indicators	Expected outcome
Computerization	Productivity increase, digitalization	k_{ICT}↑, g↑ ; g_{ICT}↑, g_{TFP}↑
1st Cost Disease	Productivity increase, job demand	g↑, ΔH↓
2nd Cost Disease	Productivity increase, job demand	$g_{public} < g_{market}$
Combined	Productivity increase, job demand, digitalization	k_{ICT}↑, g↑, ΔH↓ ($g_{public} < g_{market}$)

Table 4. Variable overview.

Variable	Description	Indicator of
ΔH	Work hour development (1998-2015)	Job demand
g	Total growth per hour worked (1998-2015)	Productivity
g_{ICT}	ICT growth (1998-2015)[8]	Computerization
g_{TFP}	Total Factor Productivity growth (1998-2015)	Productivity
k_{ICT}	ICT capital intensity (2014)	Computerization

Furtheremore, the hypotheses are tested with OLS regression with significance levels of *, ** and ***, corresponding to p = 10%, 5% and 1%, respectively. [9] To test the second cost disease hypothesis, a two-sided t-test is performed. All variables in Table 4 are *relative the country average* and all *growth accounts are given per work hour.*[10] Comparisons between country averages are motivated for two reasons: first, to put focus on the relative growth between sectors, as this is Baumol's main point. Secondly, to facilitate visual analysis of all countries simultaneously, which otherwise would be distorted by differences in general growth.

Furthermore, both g and g_{TFP} are used as indicators of productivity. The main reason for this is that g is believed to correspond best to Baumol's definition of productivity, whereas g_{TFP} would correspond best to the expected technological benefits from ICT. In addition to this, the preferred parameter for measuring computerization – g_{ICT} – is only the proportion of g that is due to ICT-capital, thus a comparison between these parameters would only be an indirect way of measuring the ICT capital intensity. Thus, g is tested towards the ICT capital intensity of

[8] Sweden and Italy did not have any numbers for ICT in 2015 but the calculations were made identically as for the other countries, resulting in slightly underestimating g_{ICT} in these countries (by approximately 6%).

[9] The software used was Microsoft Excel, Analysis ToolPak: Regression.

[10] The country average of the total economy excludes sectors T and U, see Jäger (2017).

2014, k_{ICT}. This variable is believed to be fairly representative of how digitized the sector is today, however it might be less representative for the earlier part of the time period. However, it excludes any effects of changes in labor composition and attributes parts of TFP to ICT. These problems are partially addressed by also comparing g_{TFP} to g_{ICT} for the computerization hypothesis, where the technological progress in proportion to ICT is estimated.

The market economy is considered to be all sectors except for L, O, P, Q, T and U (Jäger, 2017). To facilitate a more detailed sectoral analysis between the market and the public sector, the top three sectors within each sector, ranked by work hours in 2015, are selected to give a representative sample. This selection of large sectors might result in some bias due to their size, however, since they have a larger impact on the economy than smaller sectors it can be considered appropriate to give them more attention. In addition, all sectors are somewhat scattered and heterogenous groups in themselves, thus any study on this level always risks missing effects found in smaller segments. This bias problem might therefore be considered as a relatively small addition to an already existing problem.

Some of the sectors also have data provided on a more detailed level; C, G, H and J to be specific. In all studies, MARKT, O-U, R-S and TOTAL are removed to not double count sectors. In addition, it should be noted that some industries are believed to be inherently more dependent on ICT than others. Therefore, they are divided into 'pure IT', i.e. IT and other information services (62-63), other very ICT-intensive industries, 'high IT' (see Table 5), and all other sectors on detailed level, 'normal'. This division is made to see if there is any significant difference between these groups, to distinguish if any general trend of ICT productivity is only due to the very ICT insensitive sectors. The selection of high IT sectors is somewhat arbitrary, though it can be motivated objectively by sectors that work directly with ICT equipment (26-27, 58-60, 61) and those with abnormally high ICT-capital (K). To see if the level of detail affects the results, the hypotheses are tested on multiple levels, see Table 5.

Table 5. Overview of different selections of sectoral detail level.

Level	Description
Detailed	All sectors, number level where possible
Normal	Same as 'detailed', but excluding High IT (26-27, 58-60, 61, K) and 'pure IT' (62-63)
Rough	All sectors, on letter level
Industry	Only manufacturing industry, on number level
Industry w/o 26-27	Same as 'industry' but excluding 'high IT' (i.e. 26-27)

4.2 Variable Processing

4.2.1 Work hour development: ΔH

H_EMP is defined in EU_KLEMS as the total hours worked by persons engaged (thousands). To measure the relative changes between sectors over time, the hours worked in each sector (H_EMP_{sector}) are divided by the hours worked in the total economy (H_EMP_{total}) to calculate each sector's relative share of total employment (H_EMP_{rel}):

$$\mathrm{H\_EMP}_{rel} = \frac{\mathrm{H\_EMP}_{sector}}{\mathrm{H\_EMP}_{total}} \tag{4-1}$$

By comparing this parameter between the selected years, ΔH expresses the work hour development in each sector, see Eq. (4-2):

$$\Delta\mathrm{H} = \mathrm{H\_EMP}_{rel(2015)} - \mathrm{H\_EMP}_{rel(1998)} \tag{4-2}$$

For example, a sector with a positive number would have a relatively larger amount of work hours in 2015 compared to 1998, indicating that job demand has increased.

4.2.2 Relative growth parameters: g, g_{ICT} and g_{TFP}

The EU KLEMS LP1 data is given as annual growth, thus to be able to calculate the compound annual growth over a longer time period correctly the following expression was used:

$$\mathrm{g}_{LP1} = \left(\prod_{n=1998}^{2015} (1 + 0.01 \cdot LP1_n)\right)^{\frac{1}{17}} - 1 \tag{4-3}$$

To avoid measuring the general growth of each country, the growth of each sector was compared to the average growth of the total economy, see Eq. (4-4):

$$\mathrm{g} = \mathrm{g}_{LP1(sector)} - \mathrm{g}_{LP1(total)} \tag{4-4}$$

For example, if g is positive for a sector, the growth has been higher than the average of the total economy 1998-2015.

4.2.3 ICT capital intensity: kICT

The EU KLEMS Kq data is the real fixed capital stock. First, the absolute ICT capital intensity using numbers for 2014 is calculated as:

$$\mathrm{k}_{ICT\_abs} = \frac{\mathrm{k}_{IT} + \mathrm{k}_{CT} + \mathrm{k}_{SW}}{\mathrm{k}} \tag{4-5}$$

By comparing this parameter to the average in the economy, the (relative) capital intensity is calculated as:

$$\mathrm{k}_{ICT} = k_{ICT\_abs(sector)} - k_{ICT\_abs(total)} \tag{4-6}$$

For example, if $\mathrm{k}_{\mathrm{ICT}}$ is positive for a sector, the ICT capital intensity is higher than average in the total economy 2014.

5. Results

In this section the results from the study are reported. First, the initial setup for the study is presented, followed by the method and corresponding results for each hypothesis in the following order: 1) Computerization, 2) The Cost Disease 1+2, and 3) Combined.

5.1 Initial Setup

The three largest sectors in the market economy and the public economy was determined by sorting all sectors by their relative size of work hours in 2015. The result was the same for all countries and the representative sectors are displayed in Table 6 together with their share of work hours and the total ICT capital intensity of the economy.

Table 6. Largest sectors in 2015 by work hours.

Sector \ Country	US	UK	IT	FR	DK	SE
C: Total manufacturing	9.5%	9.1%	15.8%	9.9%	11.1%	12.9%
G: Wholesale and retail trade; repair of motor vehicles and motorcycles	13.4%	14.6%	16.0%	13.8%	15.2%	12.8%
M-N: Professional, scientific, technical, administrative and support service activities	12.9%	16.7%	11.8%	14.6%	10.9%	11.1%
Market	35.8%	40.4%	43.5%	38.3%	37.2%	36.8%
O: Public administration and defense; compulsory social security	8.2%	4.6%	4.6%	7.9%	5.6%	5.4%
P: Education	7.0%	7.0%	4.0%	5.6%	7.8%	9.1%
Q: Health and social work	12.6%	11.3%	6.8%	13.2%	16.8%	16.3%
Public	27.8%	23.0%	15.4%	26.8%	30.2%	30.9%

Sample representation of total economy	63.6%	63.4%	58.9%	65.1%	67.4%	67.7%
ICT capital intensity of total economy	*3.2%*	*2.9%*	*1.7%*	*2.4%*	*2.7%*	*3.5%*

As can be seen, most of these sectors are diverse and include a multitude of different jobs. Especially M-N, which can be presumed to be a complement to especially C, but in practice all other sectors. Additionally, it should be noted that what is here regarded as the public sector is somewhat rough and partially incorrect; e.g., college education in the US is (partially) privately funded, whereas it is publicly funded in Sweden.

Moreover, this sectoral division of work hours can be used as an indicator for differences between the countries. For starters, it appears as Esping-Andersen's (1990) division is not obviously the best way to sort these nations in this respect; especially Italy and France do not appear to belong to the same category. In general, Italy stands out: they have a significantly higher industrial sector (C) that the other nations, and their health and social sector (Q) is significantly lower. The latter can possibly be attributed to that Italy's activities of households as employers (T) corresponds to 5.64% of the total employment, which can be compared with an average of 0.39% in the other countries.

In addition, it appears as US and France have a significantly higher spending in O. Speculating in the case of US, it could be due to their relatively high defense budget, and in France as a part of their social security system. It could however be noticed that the social-democratic regimes, i.e. Denmark and Sweden, appears to have higher public spending (as expected), especially in health and social work (Q). It can also be noted that the ICT capital intensity in the economies differ substantially: Sweden has almost twice as high ICT capital intensity as Italy, indicating that Sweden is a significantly more digitalized economy.

This analysis could be pursued further, however, this is not the main topic of the thesis. The objective of this setup was to see if the sectors have similar attributes in different countries and/or if this could be correlated to their welfare funding model. As can be seen, the countries appear to follow similar patterns, but they do not seem to be constrained by their identified welfare regime. Thus, any identified trends should not be considered as the result of a specific welfare regime, but as a more general trend.

Finally, to round off the setup for the hypothesis testing, a motivation to remove some data points is provided in Table 7.

Table 7. Overview of removed data points.

Country (sector)	**Motivation**
SE (19)	g, g_{TFP} < -200%, presumably a data error
Studies on g, k_{ICT}	
DK (19), IT (19)	g < -10%, probably due to external effects
All (U, T), FR (45-53), IT (45-53), SE (20-21, 49-53), US (45, 61)	Lacks data on k_{ICT}
Studies on g_{TFP}, g_{ICT}	
FR (S), SE (O, P, Q, S), US (13-15)	LC $\geq$ 1%, appears to be a redefinition of LC which results in corresponding decreases in g_{TFP}
DK (19, B, 53), FR (19), IT (19), SE (B), UK (19, B)	g_{TFP} < -5%, probably due to external effects

5.2 The Computerization Hypothesis

The objective of this test is to examine if there is a correlation between ICT and productivity growth. The expected correlation of the variables is as follows:

1) $k_{ICT}\uparrow$ - $g\uparrow$: higher ICT capital intensity leads to higher productivity growth
2) $g_{ICT}\uparrow$ - $g_{TFP}\uparrow$: higher growth attributed to ICT capital leads to higher TFP growth

It should be noted that these tests will not indicate if ICT is a GPT or if it affects growth in general, only if ICT-intensive sectors have a higher productivity growth than those with less intensity.

Using the division between 'pure IT, 'high IT' and 'normal', the relation between k_{ICT} and g for all sectors is presented in Figure 9, and for g_{ICT} and g_{TFP} in Figure 10.

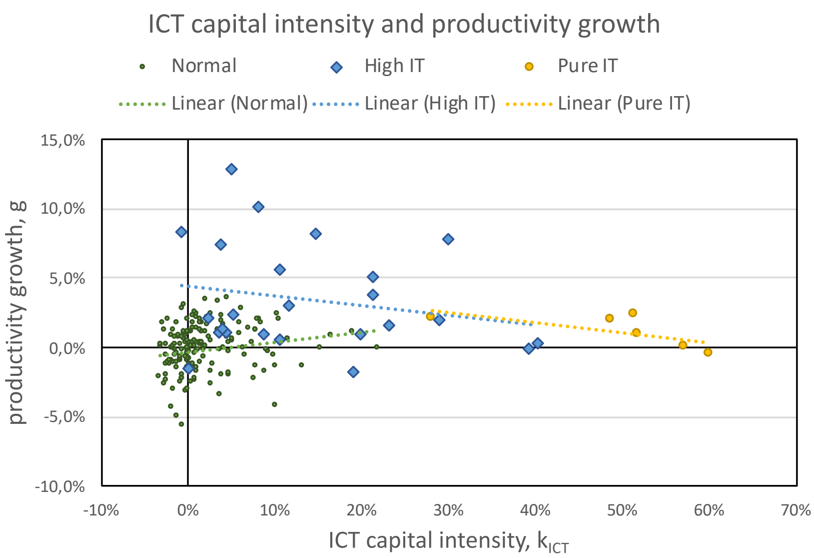

Figure 9. Correlation between k_{ICT} and g for all sectors at a 'detailed' level.

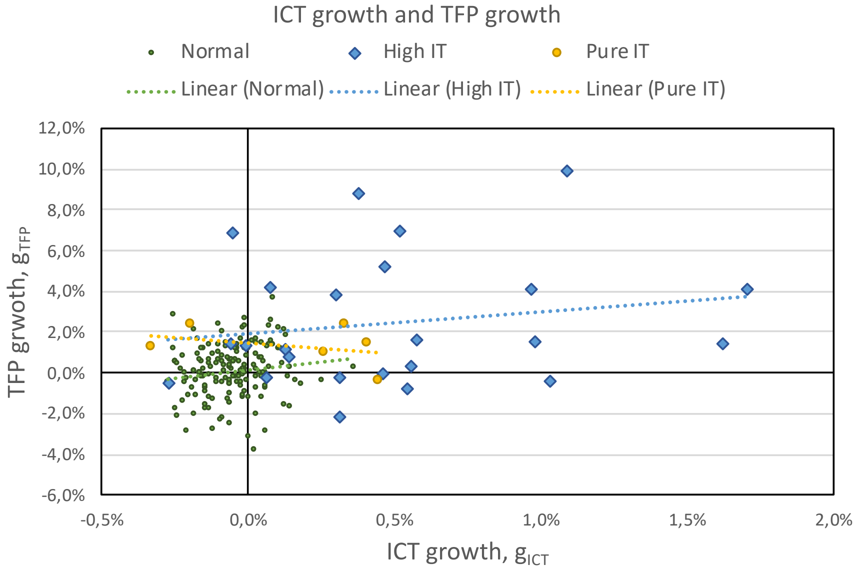

Figure 10. Correlation between g_{ICT} and g_{TFP} for all sectors at a 'detailed' level.

Some interpretations of the graphs are warranted. In Figure 9, all sectors to the left of the vertical zero line have a lower ICT capital intensity than average, whereas all sectors above the horizontal zero line have a productivity growth above average. The graph is skewed heavily to the right, which is reasonable, since the average ICT capital in all economies are 1.7-3.5% and thus the lowest relative intensity could be -3.5%, whereas the highest could be 96.5%.

In Figure 10, all sectors to the left of the vertical zero line have an ICT contribution to growth below the average and all sectors below the horizontal zero line have a TFP growth below average. Here, it appears as some of the 'pure IT' industries (i.e. 62-63) have ICT growth below average, which is contrary to expectations. However, this is at least partially explained by their position in Figure 9: if there is no productivity growth at all, very little of it can be attributed to ICT capital. The reason for the small growth of the ICT industries could possibly be due to price decreases of ICT products. In general, it is clear that the IT intensive industries appear well above average in TFP growth, as the linear fits are far above the horizontal zero line.

As expected, both 'high IT' and 'pure IT' covers the positive outliers. Disregarding these, there still remains some possible misrepresentation in the data; e.g. the ICT capital intensity in heavy capital sectors naturally becomes very low. Likewise, the lowest productivity growth – and TFP growth – can be found in the mining and quarrying industry (B), possibly due to external factors such as mineral prices.

The slope of the trendlines are not particularly interesting for ‘high IT’ and ‘pure IT’ as their sample sets are small, and it is a trend amongst outliers. However, there appears to be a small positive trend for the ‘normal’ sectors. To analyze these in more detail, OLS regressions were made on the different sample sets. The result from these are presented in Table 8 and Table 9.

Table 8. Linear regression with g as the dependent variable.

Variable	**Detailed**	**Normal**	**Rough**	**Industry**	**Industry w/o 26-27**
Intercept	0.0015 (0.002)	-0.0028* (0.0015)	-0.0069*** (0.0018)	0.0087*** (0.0030)	0.0070*** (0.0022)
k_{ICT}	0.044*** (0.016)	0.056* (0.031)	0.091*** (0.020)	0.133* (0.058)	0.073 (0.048)
N	174	144	102	62	56
Adjusted R^2	0.036	0.015	0.16	0.06	0.022

Table 9. Linear regression with g_{TFP} as the dependent variable.

Variable	**Detailed**	**Normal**	**Rough**	**Industry**	**Industry w/o 26-27**
Intercept	0.0031** (0.0012)	0.0008 (0.0011)	-0.0009 (0.0012)	0.0090*** (0.0022)	0.0056*** (0.0018)
g_{ICT}	2.476*** (0.426)	1.318 (0.855)	1.837*** (0.488)	5.744* (1.945)	2.147 (1.631)
N	190	160	106	61	55
Adjusted R^2	0.15	0.01	0.11	0.11	0.01

As could be visualized in both figures, on a ‘detailed’ level there is a positive correlation between ICT capital intensity and productivity growth, as well as between ICT growth and TFP growth; they are both significant at a 1% level. However, in both cases the null hypothesis cannot be rejected if the ICT-intensive industries are removed from the sample set (i.e. ‘normal’ and ‘industry w/o 26-27’). From this data, it appears as the gains from relatively high investments in ICT do not result in significant TFP growth for ‘normal’ industries, though it correlates with g on a 10% significance level. However, ICT-intensive sectors have experienced a higher productivity growth than other sectors, thus, for the whole economy, the computerization hypothesis survives the test on both ‘detailed’ and ‘rough’ level. It should be noted that the main difference between these levels is that the former group gives a larger weight to e.g. manufacturing industries (11 groups) and ICT industries (3 groups), indicating that identified correlations here should not be interpreted for the economy as a whole, only for sectors in general.

In addition, some of the intercepts show significance. The origin of this effect is that the sectors have not been properly weighted, since it is expected that the intercept should be zero after subtracting the country averages. Thus, removing the 'High IT', i.e. 26-27, from industry do show the expected effect by decreasing the intercept, indicating that this group has a higher g and g_{TFP} than the other industries.

It should also be noted that the adjusted R^2 is low. This indicates that e.g. ICT intensity on its own is not a good predictor of the growth of a sector, and when the ICT-intensive industries are removed from the sample, the regression can hardly predict anything (adjusted $R^2 = 0.01$). Seen from this perspective, 'rough' appears in general to be a stronger predictor than 'detailed' with an adjusted R^2 of 0.16 and 0.11 for g and g_{TFP}, respectively. This is possibly due to the larger influence of ICT-intensive sectors and the greater weight given to the scattered industry sector – which in itself has a very low adjusted R^2 – on the 'detailed' level.

In conclusion, more ICT intensive sectors have a higher productivity growth, and sectors with high ICT growth also have higher TFP growth. Thus, both tests supported the hypothesis, though the explanatory value is low. Furthermore, 'rough' appears to generally generate the best predicted values.

5.3 The Cost Disease Hypotheses

In this test, the two cost disease hypotheses are examined:

1) $g\uparrow$ - $\Delta H\downarrow$: higher productivity growth will lead to a smaller share of work hours
2) $g_{public} < g_{market}$: public sectors (O, P, Q) will have less productivity growth than other sectors

To test the first hypothesis, the relation between productivity increase and work hour development for all sectors 1998-2015 can be found in

Figure 11 and for large sectors – C, G, M-N, O, P, Q – in Figure 12 (note the different scales). Here, sectors with an increased share of work hours in 2015 compared to 1998 will be found above the horizontal zero line, and sectors with a relatively high productivity growth 1998-2015 to the right of the vertical zero line. Thus, a downward slope is expected, i.e. that progressive sectors are in the bottom right corner and stagnate sectors to the top left.

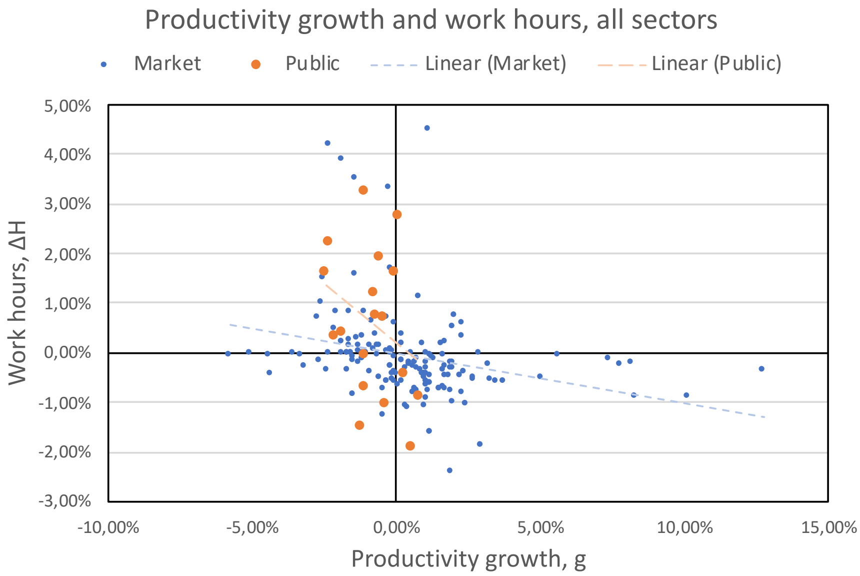

Figure 11. Correlation between productivity growth and work hour change 1998-2015 for all sectors on a detailed level.

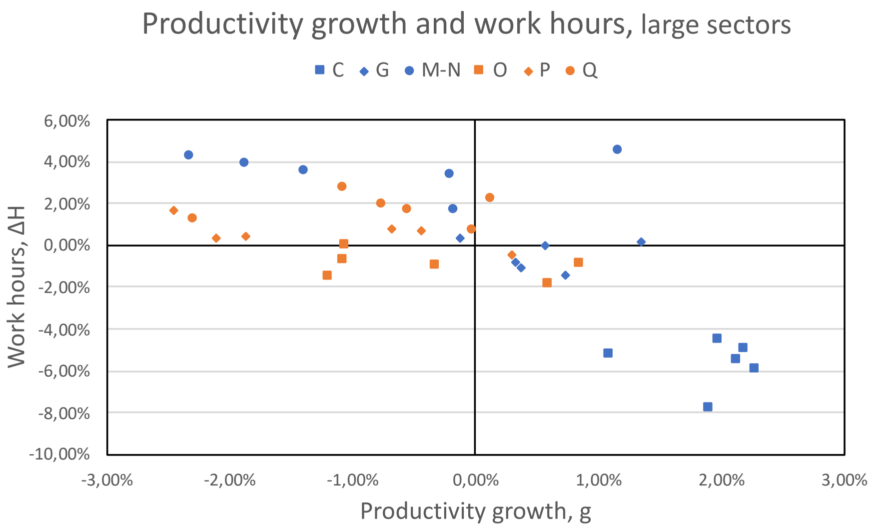

Figure 12. Correlation between average productivity growth and relative work hour change for large sectors.

As can be seen in both figures, the public sectors generally have a productivity growth well below average and they tend to have small bias for increasing their share of work hours. Moreover, the trend for all sectors appears to be that a higher productivity correlates with relatively fewer work hours according to Baumol's theory. In Figure 12, the spread between countries can be visualized, however, in general it appears as the sectors behave similar:

- Total manufacturing (C) have a higher productivity growth and relatively fewer work hours. This is expected, since it has served as the example of a progressive sector where adaption of automation technologies is relatively easy.

- Whole sale and retail trade; repair of motor vehicles and motorcycles (G) shows positive productivity growth, however in general no substantial decrease in work hours.
- Professional, scientific, technical, administrative and support service activities (M-N) appears to be a relatively average sector in all countries.
- Public administration and defense; compulsory social security (O) is the only public sector decreasing their share work hours. The two countries with positive productivity growth are France and Italy, which possibly could be attributed to their welfare regime.
- Education (P) appears to be stagnant as expected for public sectors, i.e. lower productivity and more work hours, with an exception for Italy.
- Health and social work (Q) also appear stagnant as expected, with exception for UK.

The results from linear regression confirms the hypothesis that sectors with higher productivity growth decrease employment and can be found in

Table 10. Once again, 'rough' appears to provide the best explanation and also the slope is significantly steeper than for 'detailed'. However, though the trend is the same on industry level, the slope is less steep, it is less significant, and it has a lower explanatory value.

Table 10. Linear regression on different levels with ΔH as the dependent variable.

Variable	Detailed	Rough	Industry
Intercept	-0.0002 (0.0008)	-0.0069*** (0.0018)	-0.0049*** (0.0005)
g	-0.105*** (0.030)	-0.405*** (0.098)	-0.040* (0.021)
N	145	102	62
Adjusted R^2	0.07	0.16	0.07

To further test if *productivity* is lower in public sectors, three two-tailed t-test were made on a group consisting of the sectors O, P and Q. In the first test, the public sectors were tested against the hypothesis H_0: $\mu = 0$, i.e. the average of the total economy. A problem with this test is that the OPQ sectors also affects the average, thus two other tests were made testing OPQ towards all other sectors on 'rough' and 'detailed' level. The results from these tests are presented in Table 11. Here it can be seen that the two-sided test towards the average is unbiased and significant and thus the null hypothesis can be rejected. These later tests might then appear as unnecessary, however, they once more demonstrate the importance of sector division. For example, on ‘rough’ level, the mean is below zero, whereas it on ‘detailed’ level is above. The reason for this is still that the the industry sector is weighted significantly higher in ‘detailed’ than in ‘rough’.

Table 11. Result of a two-tailed t-test of the public sector’s (O, P, Q) productivity growth compared to 0, rough and detailed level.

Variable	O, P, Q	**0**	**Rough**	**Detailed**
Mean (S.E)	-0.0078*** (0.0023)	0*** (0)	-0.0028* (0.0021)	0.0052*** (0.0020)
N	18	-	84	156
t-stat (O, P, Q)	-	-3.41	-1.61	-4.25
p-value	-	0.0033	0.11	9.1E-5

In conclusion, this test supported the hypotheses that higher productivity growth correlates with a lower share of work hours on and that productivity growth is less prevalent within the public sector. Once again, ‘rough’ achieves a higher explanatory value than ‘detailed’.

5.4 The Combined Hypothesis

In this final test, the combination of all the earlier hypotheses were examined:

> $k_{ICT}\uparrow$, $g\uparrow$, $\Delta H\downarrow$; $g_{public} < g_{market}$: High ICT capital intensity correlates with high productivity growth and a smaller share of work hours. Also, as productivity growth is lower in public sectors, they will have a larger share of work hours.

This can be plotted in a bubble diagram with ICT capital intensity on the x-axis and productivity increase on the y-axis. In addition, bright large bubbles correspond to a high work hour decrease and dark large bubbles to a high work hour increase. According to the hypothesis, large bright bubbles are expected to be found in the top-right corner. In addition, since public sectors have less productivity growth than market sectors, they are expected to be below the horizontal zero line. The results for all sectors are presented in Figure 13 and for the large sectors in Figure 14 (note the different scales of the bubbles).

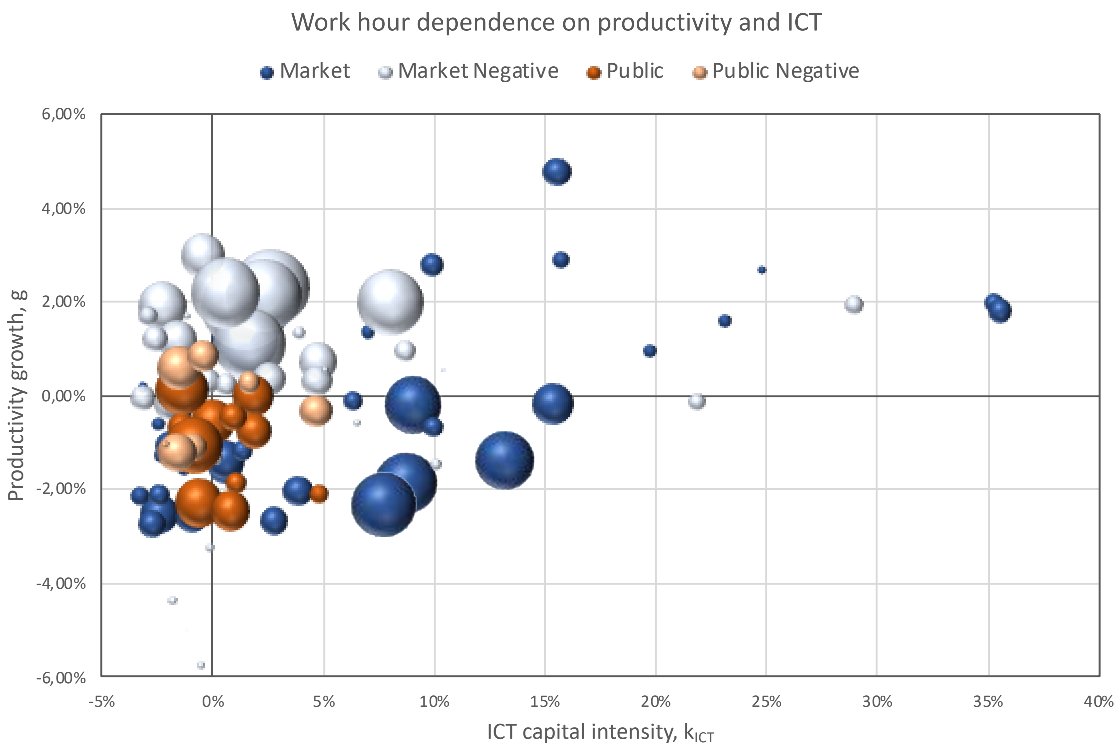

Figure 13. Correlation between ICT capital intensity, productivity growth and work hour for all sectors on 'rough' level.

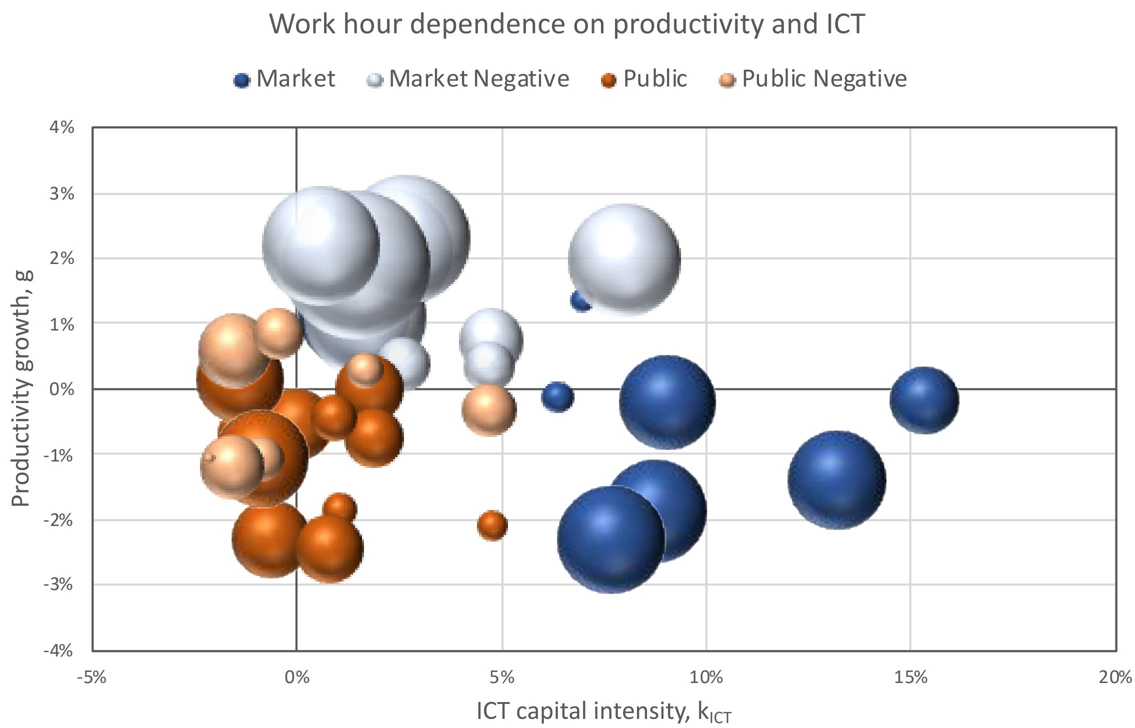

Figure 14. Correlation between ICT capital intensity, productivity growth and work hour for all sectors on a large sector level.

As can be seen in both the figures, the hypothesis appears to be correct: the public sectors are found in the bottom (left) corner, in general with increased work hours. The exception is still the O sector, however, Baumol's theory does not say that all public sectors necessarily has to be stagnant. The market sectors are spread out, and in the bottom right corner of Figure 14 is professional services (M-N) in correspondence with earlier findings.

To test the hypothesis, linear regressions were made with ΔH as dependent variable and g, k_{ICT} and a dummy variable for public sectors as explanatory variables. Since the public sectors are not a part of 'industry', this level was excluded from this test. The result can be found in Table 12, which confirm also this combined hypothesis, where adjusted R^2 is up at 0.22 for the rough selection. It should be noted that this regression only tests how well the changes in employment can be described by ICT and growth, however, one way to measure growth could possibly be by the amount of labor needed to produce a specific output, disregarding capital input.

Table 12. Linear regression with ΔH as dependent variable and g, k_{ICT} and a dummy variable for public sectors as explanatory variables.

Variable	Detailed	Rough
Intercept	-0.0010 (0.0009)	-0.0061*** (0.0021)
k_{ICT}	0.0186*** (0.0066)	0.0770*** (0.0231)
g	-0.1277** (0.0303)	-0.5279*** (0.1018)
Public (dummy)	0.0058** (0.0024)	0.0074* (0.0044)
N	174	102
Adjusted R^2	0.13	0.22

In conclusion, it appears as the sectoral data supports also the fourth hypothesis, i.e. the claim that ICT capital intensity correlates with higher productivity growth and a decreased share of work hours. Moreover, the public sectors – O, P and Q – have a significantly higher share of work hours than the other sectors. Specifically, this applies to P and Q, i.e. the education and health sectors, and it also appears to apply to M-N, the professional service sector.

6. Discussion

The results from the study showed that all the explanatory variables were significant, yet their explanatory value was low. This could be visualized by the spread of data points in the figures as well as in the adjusted R^2 calculations. Naturally, all other factors but the measured ones were overlooked, thus any external effects such as outsourcing or oil prices – even other capital investments – were dismissed in the study. Thus, any claims of causality should be considered with great care. However, it was also believed that the effects of the cost disease and computerization when measured as GDP would be artificially low, thus it is possible that the real productivity growth in fact were substantially larger than was identified.

One of the main issues in the study was that computerization was modelled as ICT capital. Earlier it was mentioned that for every dollar in hardware, on average another nine dollars were invested in related software and business processes, some of them so-called intangible assets. If this average number is spread differently between sectors, it is possible that the capital intensity of ICT is a misleading figure. Also, measuring the growth over 17 years and comparing it to the ICT capital intensity in the penultimate year appears as examining if growth leads to ICT investments and not the other way around. It should also be mentioned that a different variable, e.g., ICT capital per work-hour, could have been a more appropriate indicator as it would avoiding ruling out the importance of ICT in non-ICT capital intensive sectors. On the other hand, such a number would possibly undervalue other capital, especially in non-ICT capital intensive sectors. Another way to address this could be by making a longitudinal study, however, the constantly decreasing prices of ICT equipment might substantially skew the data, and the delay of investment pay-off might be hard to attribute correctly. Once again, measuring the real economy impact of ICT appears to be notoriously difficult.

As earlier mentioned, measuring growth is very uncertain in the public sectors, since there is no market price available for their services. For example, it is possible that these sectors could experience technical growth above average and increase their output, however, if they are not paid by their output level, this growth will not be seen in the GDP numbers. Still, the fact that the public sectors have increased their share of work hours could be seen as an indication of that the demand of their services have grown faster than their relative technological progress. Also, it is of course possible that public services have less incentives to increase productivity since they are not exposed to competition and this is the reason for their comparatively low growth numbers.

Remembering the result from Frey and Osbornes study, it appeared as many jobs within e.g. the health care and education sectors will be less susceptible to computerization. Still, the idea that public services cannot gain directly from ICT development should probably be rejected, as there probably is ample room for ICT investments and general productivity improvements. Also, the fact that the public services have been less ICT intensive and had lower productivity growth historically does not imply that they have to be so in the future. Thus, it appears reasonable to expect that within the nearest future the trends will continue.

Furthermore, Baumol never claimed that the disease applies only to services in the public sector, just that they are a good example of an economic activity that is susceptible to it. However, he claimed that business services could be considered a progressive sector, though it appears as M-N is not as it has both increased its relative share of work hours and had a relatively low productivity growth. There might be many reasons for this, for example that M-N is a group that consists of many types of services, where a dominant share should be considered stagnant. Additionally, the group might be affected to other structural changes on the labor market that has not been identified in the study.

Regarding the relative supply of labor, it is not necessary that the relative cost of all human labor has to increase. The historical fact that the wage premium has not managed to increase the supply of skilled labor in accordance with demand implies that Baumol's premise of 'wages will be the same in both sectors' is less applicable in the modern labor market were certain skills are needed for certain jobs. Thus, it is reasonable to expect that e.g. the wages in service jobs with an increasingly large labor supply will not increase proportionally to the wages in the progressive sector.[11] Furthermore, the premise that productivity increases necessarily increase the wages in the progressive sector probably only holds true for jobs with a restricted labor supply. Moreover, what constitutes a progressive sector might change over time depending on what type of technology that is available and the final demand in society. Finally, the capital-labor split does not have to remain constant over time.

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[11] In this discussion, any influence of labor unions or general politics has been neglected.

As often in these kinds of discussions, there has been a large focus of the negative aspects of computerization. This could be attributed to psychological limitations, where it is easier for us to imagine what could be lost than what could be gained since we lack a vivid picture of the latter. However, technological growth is per definition desirable since it increases our alternatives and makes it possible for us to do more with less. The fact that we can replace some jobs with computers should be good, since if we still *wanted* to perform these tasks, there is no physical law that stops us. Instead, the problem lies in how the wealth of computerization is divided, a problem that is far beyond the scope of this thesis.

6.1 Further work

It is of course possible to conduct more comprehensive studies on the same theme with more countries, span over more years and weighting the influence of different sectors, however, considering the extensive studies that already have been performed on this topic there might be a limited interest for such. Nevertheless, more detailed and country-specific studies would be interesting since they might identify other trends. It could also be interesting to see if the general ICT capital intensity of a country promote certain effects.

One related study that could be of interest would be an examination of how e.g. career officers and student counselors have adapted to the scientific literature on computerization. Still, identifying better indicators of ICT influence and an economic value that is independent on market prices would probably be most relevant to advance the science om computerization and the labor market.

7. Summary

In the introduction, three questions were asked:

1) What are the characteristics of digital technologies?
2) Which tasks can be computerized?
3) What are the effects of computerization on labor productivity, employment, and the public sector?

This thesis has attempted to address these questions with various methods and at different depths. Regarding the first question, digital goods are *non-rival* and have *extremely low marginal reproduction costs*. Partially as a consequence of this, the value of digital technologies is *difficult to measure with GDP*, since they can create large benefits at low costs by inventing new solutions while destroying old businesses in the process. To answer the second question, Frey and Osborne (2013) were consulted. According to them, *most tasks can be computerized* within the coming two decades – approximately half of the present jobs in the US – but tasks strongly connected to *finger dexterity, originality and social perceptiveness* are believed to be irreplaceable within the foreseeable future.

The remaining question was addressed both in the literature survey and in the subsequent study on sectoral computerization, productivity growth and work hour development. In ALM's framework of *task-biased technological change*, computerization replaces '*routine'* tasks and complements *'nonroutine'* tasks. The effects so far in advanced economies have been that middle-income jobs have disappeared, resulting in an increasingly *polarized labor market* with more people employed in low-income and high-income jobs, however the *wages have only increased in high-income jobs*. However, as technology advances, more jobs will be susceptible to computerization; looking at the results from Frey and Osborne (2013), it appears as primarily *low-income jobs will be susceptible to computerization* within the nearest future.

In the study, it was shown with EU KLEMS data for six countries, that sectors with a relatively high ICT capital intensity 2014 also had a relatively high productivity growth 1998-2015 and a lower share of work hours in 2015 than in 1998. These results *support Baumol's cost disease*, i.e. the claim that over time, less people will work in progressive sectors. In addition, the study supported the notion that *the public sector could be considered as stagnant*, since it demonstrated relatively low productivity growth and an increased share of work hours. Looking at the computerized future – *the second machine age* – it appears likely these trends will continue. However, the study contained large uncertainties and the variables explained only small parts of the development, thus no strong conclusion can rest on the results obtained.

Appendix A: The EU KLEMS Database

Table 13. Division of EU KLEMS industries (Jäger, 2017, pp. 4-5)

34 industry list, based on NACE Rev.2 / ISIC Rev. 4		
No	**Description**	**Code**
Agg	**TOTAL INDUSTRIES**	TOT
Agg	**MARKET ECONOMY**	MARKT
1	AGRICULTURE, FORESTRY AND FISHING	A
2	MINING AND QUARRYING	B
Agg	**TOTAL MANUFACTURING**	C
3	Food products, beverages and tobacco	10-12
4	Textiles, wearing apparel, leather and related products	13-15
5	Wood and paper products; printing and reproduction of recorded media	16-18
6	Coke and refined petroleum products	19
7	Chemicals and chemical products	20-21
8	Rubber and plastics products, and other non-metallic mineral products	22-23
9	Basic metals and fabricated metal products, except machinery and equipment	24-25
10	Electrical and optical equipment	26-27
11	Machinery and equipment n.e.c.	28
12	Transport equipment	29-30
13	Other manufacturing; repair and installation of machinery and equipment	31-33
14	ELECTRICITY, GAS AND WATER SUPPLY	D-E
15	CONSTRUCTION	F
Agg	**WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES AND MOTORCYCLES**	G
16	Wholesale and retail trade and repair of motor vehicles and motorcycles	45
17	Wholesale trade, except of motor vehicles and motorcycles	46
18	Retail trade, except of motor vehicles and motorcycles	47
Agg	**TRANSPORTATION AND STORAGE**	H
19	Transport and storage	49-52
20	Postal and courier activities	53
21	ACCOMMODATION AND FOOD SERVICE ACTIVITIES	I
Agg	**INFORMATION AND COMMUNICATION**	J
22	Publishing, audiovisual and broadcasting activities	58-60
23	Telecommunications	61
24	IT and other information services	62-63
25	FINANCIAL AND INSURANCE ACTIVITIES	K
26	REAL ESTATE ACTIVITIES	L
27	PROFESSIONAL, SCIENTIFIC, TECHNICAL, ADMINISTRATIVE AND SUPPORT SERVICE ACTIVITIES	M-N
Agg	**COMMUNITY SOCIAL AND PERSONAL SERVICES**	O-U
28	Public administration and defence; compulsory social security	O
29	Education	P
30	Health and social work	Q
Agg	**ARTS, ENTERTAINMENT, RECREATION AND OTHER SERVICE ACTIVITIES**	R-S
31	Arts, entertainment and recreation	R
32	Other service activities	S
33	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	T
34	Activities of extraterritorial organizations and bodies	U

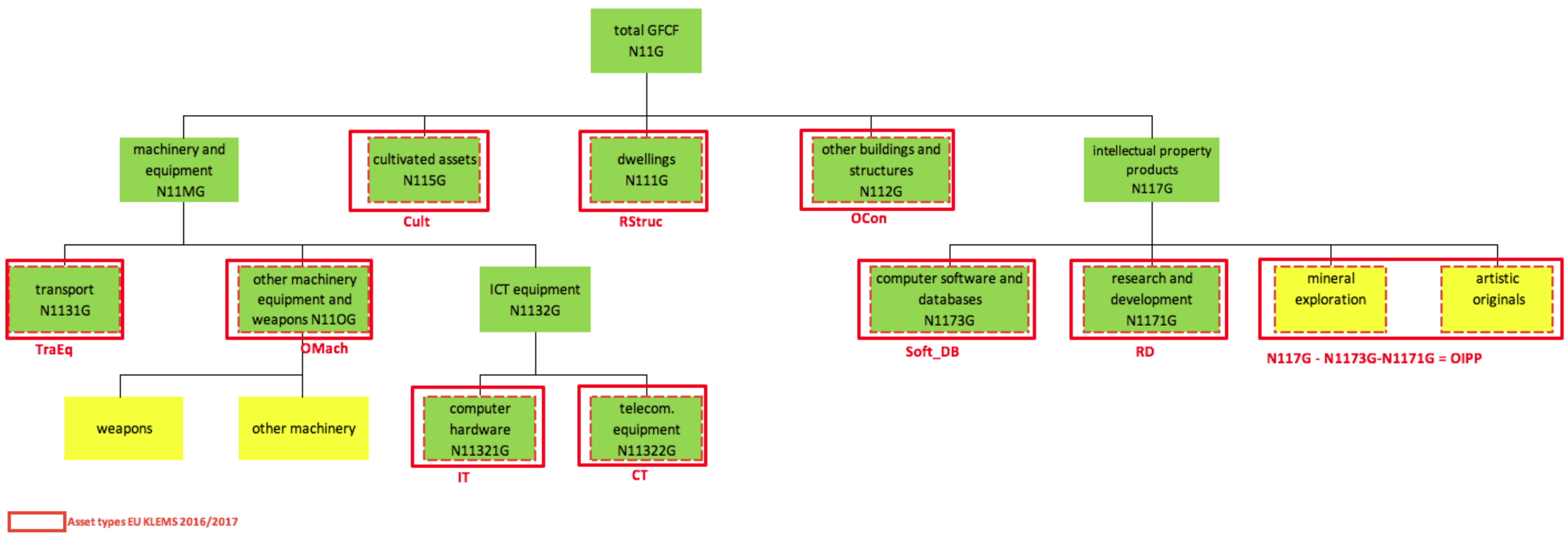

Figure 15. EU KLEMS division of capital. ICT assets are considered to be computing equipment (IT), communication equipment (CT) and software (Jäger, 2017, p. 7)

Appendix B: Bottlenecks to Computerization

*Table 14. Frey and Osborne's selection of O*NET variables that indicates bottlenecks to computerization (2013, p. 31).*

Computerisation bottleneck	O∗NET Variable	O∗NET Description
Perception and Manipulation	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
	Cramped Work Space, Awkward Positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?
Creative Intelligence	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Fine Arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.
Social Intelligence	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behavior.
	Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.

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