On the Eonomic Purpose of General Purpose Technologies: A Combined Classical and Evolutionary Framework

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5 April 2013

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Abstract

General purpose technologies (GPTs) are technical breakthroughs that are able to spur growth via their pervasive use in the economy. This paper attempts to study the effects of these innovations for the economic system on an empirical and theoretical level. A structural decomposition analysis for Denmark from 1966 to 2007 tracks the impact of the current GPT, the information and communication technology (ICT), on aggregate and sectoral labor productivity growth. Findings show that the broad diffusion of ICT affected growth significantly after 2000, owing to technical change, substitution and capital deepening, and can be associated with skill-induced wage dispersion. The diffusion process of a GPT is subsequently reconstructed by an evolutionary multisectoral framework: The Sraffian input-output approach is combined with the replicator dynamics approach of evolutionary game theory. Technical unemployment, transitional wage inequality and decelerating economic growth after the appearance of a GPT can thereby be explained.

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1 Introduction

By 1900, 38 per cent of vehicles in the U.S. were electric; 40 percent were steam powered and only 22 percent used gasoline. However, because of the limited driving range of electric vehicles and the lacking infrastructure for recharging, the technical advances in internal combustion engineering literally drove the rise of gas-powered automobiles. In 2004, automobiles and light trucks in the USA were responsible for nearly half of all greenhouse gases emitted by automobiles globally, according to a recent study by DeCicco and Fung (2006). Back in 1900, if innovative activities would have been channeled to the prevailing technology, the economy and the environment would have developed along a different, probably more sustainable, path. So history matters and some innovations are able to make history.

This is particularly the case of general purpose technologies (GPTs): major technological breakthroughs that shift physical restrictions and spur growth via their pervasive use in the economy. Prominent examples are the steam engine and electricity, and lately the new information and communication technology (ICT). To understand the inter-sectoral spill-over effects by the emergence of a GPT respectively by technical change within a GPT-producing sector therefore facilitates the understanding of economic and social consequences of technical progress. For instance, the productivity slowdown of advanced economies (especially of the U.S.) experienced in the 1980s, followed by substantial growth in the following decade, can be linked to some extent to the rise of ICT: Basic arguments for the slump brought about by ICT were the irreversibility of tailor-fit inputs, obsolescence of capital and a short supply of skilled labor (Helpman, 1998).

On an empirical level, a wide spectrum of studies have dealt with the immediate and long term effects of ICT on productivity growth. Jorgenson et al. (2007), for example, analyzed the industry sources of growth resurgence in the U.S. for the period 1960 to 2005. They identified IT as an important source for both capital deepening and total factor productivity growth in the late 1990s and after 2000. In a similar study Basu and Fernald (2007) found that industries with higher demand for ICT capital in the 1987–2000 period also had higher TFP growth rates in the

2000s. Inklaar and Timmer (2007) compared seven economies[1] with regard to industry output, input and multi-factor productivity (MFP) levels. They showed that the U.S. used twice as much ICT-capital than Anglo-Saxon countries where production tends to be more labor-intensive. This high level of IT-capital can be found across all sectors of the American economy. In a recent article, Jorgenson and Timmer (2011) show that the rapid productivity growth (in terms of MFP) in the European Union, the U.S. and Japan is accompanied by the growing role of service sectors, the decline of the labor share in value-added, and the increased use of IT-capital across all regions and sectors.

Even though the ICT revolution, starting in the U.S. in the 1960s, took several decades to show up in productivity growth in the computer-using industries, the wage of skilled workers has risen significantly from the emergence of this GPT onward. The most common explanation is that the efficient utilization of ICT makes great demands on the qualification of the workforce: New skills are required that first need to be obtained through investments in education and on-the-job-training. Thus, increasing computerization has been associated with higher levels of both skills and wages in the workforce (Majumdar, 2008; Allen, 2001; D. Autor and Krueger, 1998; E. Berman and Griliches, 1994; Krueger, 1993), as well as with the substitution of low-skilled by higher-skilled workers (Levy and Murnane, 1996). Thus, the rapid skill-biased technical change has resulted in rising wage inequality both among and within different education groups, despite an increasing supply of better qualified labor (see e.g. Murphy and Welch (1992); D. Autor and Krueger (1998)). The relation between the emergence of a GPT and skill and wage differentials have been extensively discussed in the theoretical literature (see e.g. Helpman and Trajtenberg (1998b,a) and Nahuis (2004) for a general equilibrium approach). Furthermore, Aghion and Howitt (1998a, 2002) propose a Schumpeterian framework for explaining the evolution of wage inequality.

This paper aims at contributing both to the empirical as well as to the theoretical literature. It therefore advances along two dimensions: (1) On the empirical level, the paper attempts to assess the impact of ICT (the current GPT) on ag-

[1] France, Germany, Netherlands, U.K., U.S., Australia and Canada.

gregate and sectoral productivity for Denmark between 1966 and 2007 by use of a structural decomposition analysis (SDA). Denmark is chosen due to the extent of the available data and its size, which characterizes it as a small open economy. We revert to labor productivity growth, since ICT has had a special impact on the labor market: On the one hand, labor intensity of production decreased through automation owing to ICT-capital, on the other hand the IT-boom has raised the demand for qualified workers. Combining the Sraffian (price-) with the Leontief (quantity-) system, annual changes in labor productivity are decomposed into disembodied technical change, shifts in the employment of low and high skilled labor, factor substitution, and technical change embodied in capital goods. Contrasting these results with the changes in the electricity sector allows comparing the different maturity stages of these general purpose technologies. (2) Supported by empirical evidence, the theoretical part of the article proposes a Sraffian multi-sectoral approach that is embedded in an evolutionary framework. This model is capable of reconstructing the output slump after introduction of a GPT as well as transitional wage inequality during the diffusion process of the new GPT.

The paper proceeds as follows: Section 2 introduces the inter-sectoral framework. Section 3 describes the structural decomposition analysis and the underlying data. A detailed presentation of the SDA and the industry classification can be found in the Appendix. Section 4 displays the most important results with a special emphasis on the GPT at work, ICT. In Section 5 the Sraffian static framework is augmented by the replicator dynamics approach of evolutionary game theory to gain some deeper understanding of how the inter-sectoral linkages work. Concluding remarks are given in Section 6.

2 Methodology and notation

Following Helpman and Trajtenberg (1996), *pervasiveness* is one of the three defining characteristics of a GPT (besides *scope for improvement* and *innovation spawning*). Since in this context pervasiveness is defined as the property of some technology to spread to most sectors throughout the economy, it is inevitable to analyze the economic implications of some GPT in a multi-sector setting. Therefore a classical input-output model developed by Piero Sraffa (1960) serves as the basis of our investigation. Subsection 2.1 introduces the general notation for the long-period position of the economy. This prepares ground for two further steps: Firstly, for the structural decomposition analysis outlined in Subsections 2.2 and in the Appendix A.1 for further refinement of the subsequent empirical analysis; and secondly for embedding the static model into an evolutionary framework in Section 5 to investigate dynamical aspects of the diffusion process.

2.1 A Sraffian multi-sectoral framework

In an N-sector economy, let $a_{mn} \in (0,1)$ be the amount of good m produced in sector m to produce one unit of output in sector n. A new GPT such as the ICT is accompanied by new skills necessary to operate the innovative technologies. Skill diversification, including the existence of wage premia, is considered by allowing for K different skills. $l_{mk} > 0$ then denotes the quantity of skill k necessary to produce one unit of output of sector m. The input matrices $A \in [0,1]^{N\times N}$ and $L \in \mathbb{R}_+^{N\times K}$ with coefficients a_{mn} and l_{mk} characterize the utilized technology. The n-th entry p_n of the price vector $\mathbf{p} \in \mathbb{R}_+^N$ denotes the price of commodity n. $\mathbf{w}$ is the wage vector with the k-th entry w_k denoting the remuneration of skill k. Assuming prices to be determined by unit costs of production, one gets the following price system

$$(1+r)A\mathbf{p} + L\mathbf{w} = \mathbf{p} \tag{1}$$

with normal rate of profits r (Kurz and Salvadori, 1995). Defining some commodity bundle $\mathbf{d} \in \mathbb{R}_+^N$ as *numéraire* by $\mathbf{d}^T\mathbf{p} = 1$ and wage level $w = \|\mathbf{w}\|$, the falling $w - r$ relationship

$$w = \frac{1}{\mathbf{d}^T \left(\mathbb{I} - (1+r)A\right)^{-1} L\mathbf{u}} \tag{2}$$

with constant $\mathbf{u} = \mathbf{w}/w$ can be obtained. Different kinds of technical progress can be found by studying the dynamics of the $w - r$ relationship: Harrod-neutral or purely labor-saving technical progress is represented by a clockwise rotation of the curve, whereas Solow-neutral or purely capital-saving technical progress

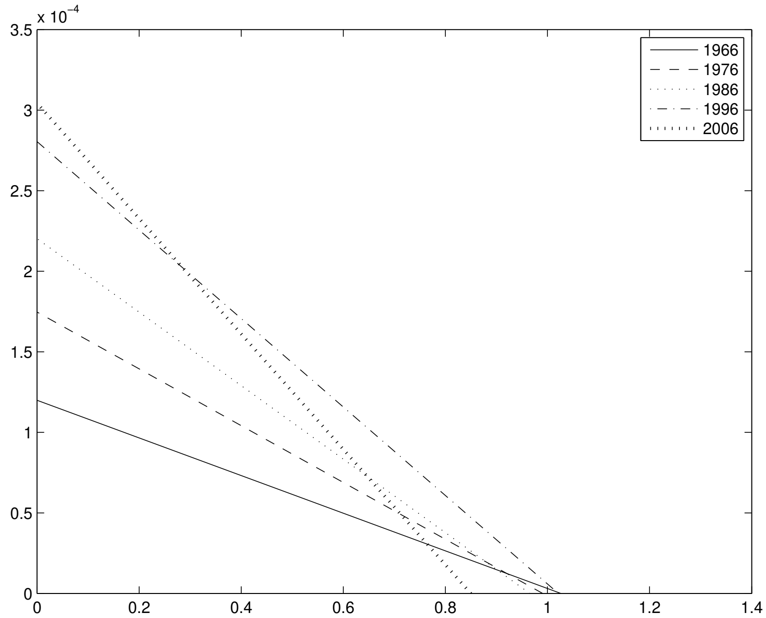

Figure 1: Wage-profit curve for Denmark from 1966 to 2006

corresponds to an anti-clockwise rotation. Hicks-neutral or factor-saving technical change leads to a parallel shift outwards. If two curves–related to different technologies–intersect, then technical progress is not unambiguous and one has to draw on actual income distribution w and r to scrutinize the sort of change (Degasperi and Fredholm, 2010, p.274).

Figure 1 shows the corresponding wage-profit-frontier for Denmark from 1966 to 2006. The intersection with the axes determines the maximum wage rate (for $r = 0$), and the maximum rate of profits (for $w = 0$) respectively. Until 1986 the curve rotates clockwise around a more or less stable rate of profit in the range of 0.92. Since this value is in reality unlikely to occur, one can conclude that in the 20 years between 1966 and 1986, labor-saving technological change took place. For 1996 the $w - r$-relationship shows unambiguous technical progress, because both intersection points moved outwards. Since then, however, the maximum rate of profits has decreased and the curves of 1996 and 2006 intersect at a rate of profit equal to 0.31. Comparing this value to the average interest rates for 2006[2] it is

[2]The EURIBOR interest rate, which is the ruling rate in the European interbanking system

clear that within a realistic range of profit rates the latter technique turns out to be labor-saving and capital-using relatively to the former production system.

In the case of a zero profit rate $r = 0$, equation (2) reads

$$\bar{w} = \frac{1}{\mathbf{d}^T \; S \; L\mathbf{u}} \tag{3}$$

with the Sraffa Inverse $S \equiv (\mathbb{I} - A)^{-1}$. The higher $\bar{w}$, the less direct and indirect labor inputs are necessary for the production of the exogenously specified commodity bundle. An increase in the maximum wage rate over time thus indicates productivity gains due to technical progress. The relative change in the maximum wage rate from one year to the next therefore provides a measure for the annual labor productivity growth:

$$g_t^l = \frac{\bar{w}_t - \bar{w}_{t-1}}{\bar{w}_{t-1}} = \bar{w}_t \left(\frac{1}{\bar{w}_{t-1}} - \frac{1}{\bar{w}_t} \right) \tag{4}$$

This measure differs from the conventional indicator of labor productivity growth in so far as it considers not only the labor that is directly employed in the respective sector, but also takes into account the labor input in the upstream production. This means that an industry exhibits a higher labor productivity (as defined by Eq.3) whenever the supplying industries operate less labor-intensively.

Labor productivity growth is in case of innovations accompanied by the emergence of new skills and respective skill premia captured by the vector $\mathbf{u}$ in equations (2) and (3). For the simple case of two different skills, and each employed in another process within the economy, wage inequality can be calculated by

$$GINI = q_h(1 - q_h)\frac{u - 1}{1 + (u - 1)q_h}, \tag{5}$$

where q_h denotes the share of high skilled labor which is utilized by the innovative process and remunerated by some wage premium $u > 1$ relative to the low skilled labor utilized by the incumbent technology. Figure 2 graphically demonstrates the dependence of wage inequality on the share of high skilled labor with a wage

for lending money and could be thus considered as a reference value, was about 0.032 on annual average.

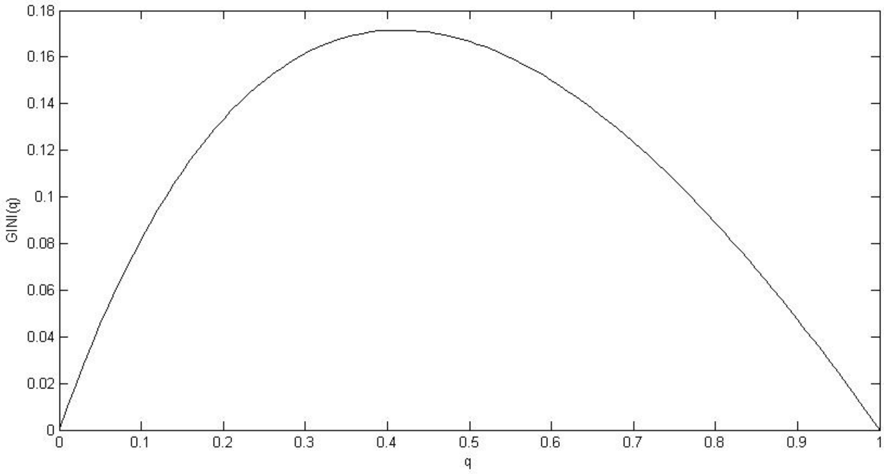

Figure 2: The GINI coefficient depending on the share of high-skilled labor

premium of $u = 2$.

2.2 Structural decomposition analysis

SDA has been a prominent tool in input-output analysis for associating changes in one variable, most often gross output or value-added, to changes in other variables (Miller and Blair, 2009; Rose and Casler, 1996; Dietzenbacher and Los, 1997, 1998). With regard to labor productivity, Yang and Lahr (2008) use two multi-regional input-output tables of China to decompose the change in labor productivity growth between 1987 and 1997 into five determinants[3] and subsequently assess the results at a regional level. In a follow-up study, the analysis is extended to further components, with a special focus on the intra- and inter-sectoral composition of final demand, and extended to the year 2005 (Yang and Lahr, 2010). The accounting framework goes back to Jacob (2003), who analyzed the growth experience in Indonesia between 1971 and 1995, distinguishing between a pre- and a post liberalization phase.

In this paper, SDA is used to break down the change in the maximum wage rate

[3]i.e. value-added, direct labor requirements, aggregate production mix, interregional trade and final demand.

(labor productivity) into its different components. Therefore the afore discussed Sraffian model is coupled with the analytical framework developed by Wassily Leontief[4].

In the Leontief system, gross output $\mathbf{x}$ is calculated from the demand side, as market clearing implies

$$\mathbf{x}^T A + \mathbf{y}^T = \mathbf{x}^T.$$

$\mathbf{y}$ gives total final demand (from private households and government, investment and exports). Furthermore, total labor demand $\mathbf{l}$ (weighted by its relative wages) can be calculated as the product of the labor intensity L and the gross output vector $\mathbf{x}$:

$$\mathbf{l} = \mathrm{diag}(L\mathbf{u})\mathbf{x} = \mathrm{diag}(L\mathbf{u})H\mathbf{y} \tag{6}$$

$H \equiv (\mathbb{I} - A^T)^{-1} = S^T$ denotes the Leontief Inverse.

Combining (6) with (3), the maximum wage rate is given by

$$\bar{w} = \frac{1}{\mathbf{d}^T\ S\ L\mathbf{u}} = \frac{1}{\mathbf{d}^T\ S\ \hat{\mathbf{l}}\ \hat{\mathbf{x}}^{-\mathbf{1}}\ \mathbf{e}} = \frac{1}{\mathbf{d}^T\ S\ \hat{\mathbf{l}}\ [\mathrm{diag}(H\mathbf{y})]^{-1}\ \mathbf{e}}, \tag{7}$$

where $\hat{}$ indicates a diagonalized vector and $\mathbf{e} \in \mathbb{R}^N$ is a vector with coefficients $e_n = 1$ for all $n = 1, \ldots, N$. Considering two different snap shots in time, from (4) and (7) labor productivity growth g_t^l can be derived as

$$g_t^l \quad = \quad w_t\ \mathbf{d}^T \Big[S_{t-1}\ \hat{\mathbf{l}}_{t-1}\ [\mathrm{diag}(H_{t-1}\mathbf{y}_{t-1})]^{-1} - S_t\ \hat{\mathbf{l}}_t\ \ \mathrm{diag}(H_t\mathbf{y}_t)]^{-1}) \Big] \mathbf{e}. \tag{8}$$

Given equation (8), the relative change in the maximum wage rate can be decomposed into four partial factors: (1) technical change as indicated by a change in the direct input matrix A ($\Delta S \equiv S_t - S_{t-1}$), (2) change $\Delta \mathbf{l} \equiv \mathbf{l_t} - \mathbf{l_{t-1}}$ of total employment, (3) substitution effect indicated by a change in A^T ($\Delta H \equiv H_t - H_{t-1}$) and (4) change $\Delta \mathbf{y} \equiv \mathbf{y}_t - \mathbf{y}_{t-1}$ of final demand. This initial decomposition is extended by differentiating between low and high skilled labor, and capital flows

[4]Interestingly, both input-output models are based upon the classical approach of value and distribution in stressing the circularity of production and were developed at about the same time (see e.g. Leontief (1928)), but independently from each other.

of ICT and Non-ICT related investments. The decomposition can be found in detail in A.1.

3 Data

3.1 National account data

Denmark is used as a case study for the following two reasons: Firstly, it is a small open economy acting as a net-importer of ICT-products[5]. ICT can therefore be analyzed from a more general perspective, since the focus is on the impact of a GPT as an input of production and not on its impact on final demand. Economies such as the U.S., Japan or Finland – which are net-exporters of ICT-products – would cause a bias with regard to this research question: It is their extensive trade with these products that affects economic development, and not primarily the pervasive use of this GPT in production.

Moreover, Statistics Denmark also provides a very good data base that fits the purpose of this work: Annual IO tables for 130 sectors in ISIC 3.2. Rev. classification, in current as well as constant prices of the year 2000, entailing domestic and import flows, and covering a long period of time (1966 to 2007). Applying the criterion of Jovanovic and Rousseau (2005a), whereby the emergence of a GPT can be dated to the year when the new technology reaches a one percent share in the industrial sector's stock equipment – which in Denmark's case was in 1979 – we can therefore also study the pre-arrival time.

The 130 sectors in the original classification were subsumed under 53 industries for the sake of better illustration of the results and in order to ensure the non-singularity of the system (see Table 2 in A.2). In the following, the years 1970 until 1972 will be excluded due to the lack of data reliability, because for these periods the results indicate a hardly viable system (i.e. with a profit-rate close to zero). Concerning the definition of the ICT-producing sector, a broad classification scheme is used, including not only the ICT manufacturing sector, but also

[5]The only exceptions are central processing units. For a detailed analysis of Denmark's position among Europe with regard to ICT activities see Koski et al. (2002).

computer related business activities and software consultancy. The following industrial and service classes comprise the notion of ICT in the scope of the present analysis: (1) Mfr. of information and communication technology (ICM): Mfr. of office machinery and computers, Mfr. of other electrical machinery and apparatus, Mfr. of radio and communications equipment etc. (2) ICT-related services (ICS): Computer activities, Software consultancy and supply.[6]

Investments in ICT capital deserve a special consideration, since most ICT products are not used up within one period, but remain in the production process. Thus the analysis needs to include investment flows as well. From 1993 to 2007 real investment matrices, in constant prices of year 2000, were available in 5 categories: (1) buildings other than residential, (2) machinery, (3) transport, (4) software, (5) construction. The classification of delivering sectors is identical to the one in the IO-scheme. However, the set of investing sectors corresponded to the national standard classification of 53 sectors, whereby 3 industries (health, research and education, culture) are further disaggregated, resulting in 56 sectors in total. In a first step, the investment matrices were re-classified according to the 53 sectors in the Sraffian classification, which was in most cases a one-to-one concordance. The only industry that needed to be split up further was electricity, since in the original classification it is presented together with gas and water supply. The assigned share was therefore derived from total deliveries of these two sectors to investment demand. However, the distribution across sectors was assumed to be the same for the electricity and the gas and water supply industry. Investment demand before 1993 was only available at an aggregate level in the aforementioned categories (1)–(5). For these years, the sectoral shares in the demand for the respective asset were calculated from the purchases of intermediate products. It is therefore assumed that sectors with higher demand for intermediate (circular) products also invest more in this technology. These estimations were backed up with investment data (industry by industry) from 1966 to 1992.

[6]This definition is widely accepted among empirical studies on ICT (see e.g. Jorgenson et al. (2007)). The division into ICT-using sectors and Non-ICT sectors was done according to the share of ICT-equipment in total investments in the year 2000 (with the threshold being 5%).

3.2 Employment data

As regards employment, total working hours of employed persons and self-employees were obtained from Statistics Denmark. For the discrimination of the labor force according to the attained education we used the Denmark labor input data provided by the EU KLEMS database (Edition 2008). This dataset comprises the shares in total hours worked as well as the shares in total labor compensation for three different qualification levels for a time-span of 26 years (1980–2005). Since these data are only broken down for 15 sectors, each subsector is approximately characterized by the same labor composition. For the purpose of this paper, only between low-skilled and higher (i.e. middle and high)-skilled workers was discriminated; no differences in age and gender are considered. For Denmark, low-skilled labor refers to basic schooling, whereas middle and high skilled labor comprises short, middle and long cycle higher education as well as vocational education and training (for further details on the labor accounts see the EU KLEMS manual, pp. 24–31). For both qualification levels, the ratio between the respective wage share and the share in total working hours is calculated in order to obtain the compensation level of the respective skills compared to the industry average.

3.3 A note on the numéraire

The empirical analysis in this paper requires the specification of a numéraire. A number of different commodity bundles were tested. By means of sensitivity analysis the specification of the numéraire is chosen whose application fits best sectoral labor productivity growth as derived from the system of national accounts. Thus, the index finally selected is the share of each industry in the net product of the year 2000. This numéraire also makes sense intuitively due to its analogy to a consumer price index, and the year 2000 is chosen as the reference period, since

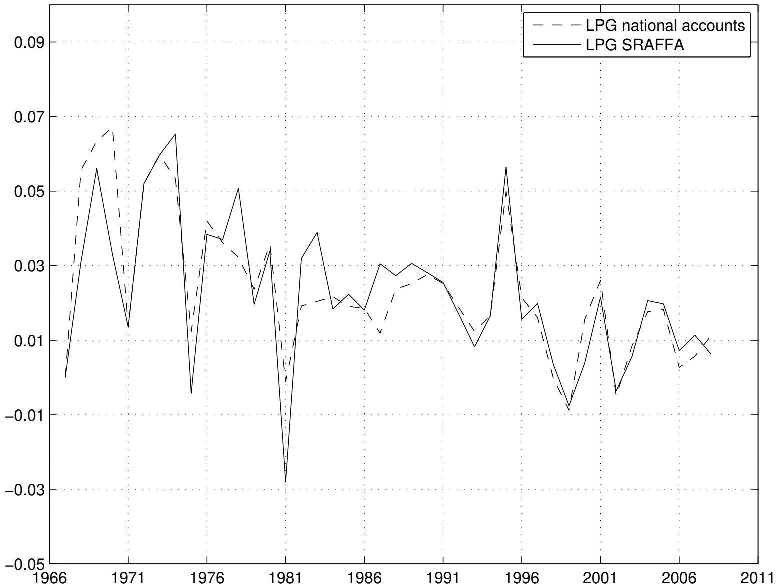

Figure 3: Growth of labor productivity (LPG) from 1966 to 2007. Figures from the Sraffian system and the system of national accounts.

the monetary IO-tables are set out in constant prices as of 2000.[7]

$$d_n = \frac{x_n - \sum_{j=1}^{53} z_{nj}}{\sum_{n=1}^{53} \sum_{j=1}^{53} y_{nj}}$$

Figure 3 presents the growth of labor productivity (LPG) obtained from the national accounts,[8] together with the productivity measure derived from the Sraffian system (solid line). The LPG measure deviates in two years (1981 and 1983) from the indicator based on national accounts, but otherwise represents a good fit to the conventional figures (with a correlation-coefficient $\rho = 0.87$).

[7]Since competitive imports are included in the transaction matrix, a negative net output is likely to occur in those periods where domestic production depends largely on imported intermediate products. Therefore it is necessary to ensure that the numéraire is strictly positive. Note that the more negative the net-product, the higher would be the positive impact of the sector on the productivity measure, thus causing a severe bias on the aggregate level.

[8]More precisely, for each period GDP at market prices is divided by total hours worked in the respective period.

4 Results and Discussion

The results of the SDA are presented first on the aggregate level (Subsection 4.1) and then with regard to the ICT (Subsection 4.2). In the latter part a discussion is included how the diffusion of ICT is linked to the evolution of wages and wage inequality.

4.1 Aggregate results

Figure 3 shows that labor productivity growth has been steadily decreasing in the past 40 years: 4.0% per annum in the 1960s compared to around 1% in the last decade. These historically low growth rates also lag behind other countries: Whereas Denmark ranked eighth among OECD countries in terms of labor productivity in 2000, it dropped back to position 12 by 2011 (McGowan and Jamet, 2012, p.5). Table 1 contains the growth rate of aggregate labor productivity on an annual average in five-year intervals from 1966 to 2007 (first line). Lines 2-9 present the decomposition of aggregate labor productivity growth into (1) technical change, (2) changes in labor composition, (3) substitution, and (4) final demand. The sign and magnitude of these factors depict the change over time in the amount of vertically integrated labor embodied in the numéraire, i.e. the physical quantities of labor directly and indirectly required in its production. While technical change led to a reduction in total labor input and thus had a positive impact on LPG until the 1990ies (except for the period 1975–1980), it was directed towards labor-using afterwards. Employment also affected productivity growth in both directions: Over the whole period of study, one can observe a decline in low-skilled labor employed, and an increase in working hours of higher-skilled workers (therefore the negative sign). However, whereas in the first decade of study the economy operated all in all labor-saving, the following decade was characterized by a rise in total working hours, caused by the strong demand for higher-skilled labor particularly in the ICT-producing and ICT-using industries. Between 1990 and 2005 the reduction in low-skilled labor outweighed the increase of higher-skilled workers. The substitution effect, i.e. the changing product mix within a sector, has had a positive impact on labor productivity growth (except for the period 1970–1980). The most important driver for LPG, however, was final demand, whereby the effect of investment demand for ICT products grew by factor seven.

The remainder of Table 1 presents the sectoral origin of growth. According to the focus of the paper, the 53 sectors are aggregated into ICT-producing, ICT-using and Non-ICT industries. As also shown in Figure 4, the impact of Non-ICT industries is significant given their share in total value-added of about 70% over this period. But it has been continuously declining, from 2.9% in the 1960s to 0.13% in the first decade of the 21st century.

On the other hand, the contribution of ICT-using industries (which account for another one third of value-added) was significant right after the emergence of the new ICT with a share in aggregate LPG of 24% or 1.99 percentage points between 1970 and 1975. This might be due to the fact that at that time office machinery already played an important role in these sectors and that the new ICT replaced the old technology step by step. In the following 20 years, the impact of ICT-using industries rose slightly (see Figure 4), until the mid 1990s, where their contribution to labor productivity growth dropped to 15%. From 2000 onwards, it seems as if ICT has finally been rejuvenating growth: ICT-using industries account for 55% (0.55 percentage points) and, in the last period of study, even for 77% (0.66 percentage points) of aggregate labor productivity growth. This rise in magnitude can directly be traced back to the ICT-producing industries, despite their small share in value added (1966: 0.6%, 2007: 4.0%). From 1966 to 1970 these five industries (three in manufacturing, two in the service sector) contributed less than half a percentage point to aggregate labor productivity. Between 1970 and 2000 their share in LPG increased moderately from 2.5% to 4%. In the most recent years of study, ICT-producing industries accounted for 0.06 percentage points of LPG (or 8%).

Turning to another general purpose technology, Table 1 also entails the effects of electricity on aggregate labor productivity growth. The era of electricity was triggered by the invention of the dynamo in 1867 and spanned from the end of the twentieth century until 1930. This time was characterized by big transformations

	1966-1970	1970-1975	1975-1980	1980-1985	1985-1990	1990-1995	1995 2000	2000-2005	2005-2007
LPG (annual average)	4.01	3.32	2.32	2.71	3.01	2.35	0.86	1.02	0.85
Factors									
Technical change	0.45	0.11	(0.47)	0.06	0.21	(0.29)	(0.40)	(1.06)	(1.63)
Labor input	0.58	2.07	(0.92)	(0.25)	0.65	0.44	(1.86)	0.08	(1.64)
-Low skilled (LS)	-	-	9.38	1.29	1.51	1.45	0.17	0.38	(25.14)
-High skilled (HS)	-	-	(10.31)	(1.54)	(0.86)	(1.01)	(2.03)	(0.30)	23.50
Substitution	11.51	(11.65)	(0.92)	0.03	0.23	0.30	0.48	1.08	1.72
Final demand	(8.53)	12.78	4.65	2.87	1.92	1.90	2.64	0.92	2.40
-ICT products	(0.14)	0.02	0.07	0.16	0.22	0.13	0.39	0.09	0.19
-Non-ICT products	(8.40)	12.76	4.58	2.71	1.70	1.77	2.25	0.83	2.21
Industries									
ICT-producing	0.04	0.11	0.08	0.09	0.08	0.11	0.03	0.05	0.06
ICT-using	1.07	1.22	0.55	0.76	0.83	0.68	0.13	0.55	0.66
Non-ICT	2.89	1.99	1.70	1.88	2.10	1.59	0.67	0.40	0.13
-Electricity	(0.02)	0.04	0.01	0.02	0.01	0.00	0.00	(0.01)	(0.01)

Table 1: Growth in aggregate labor productivity and the growth factors. All figures are average annual percentages. The industry classification is defined in the appendix. ICT includes Mfr. of ICT equipment and Computer and related activities.

in the economic system, as new products and industries arose and the industry organization changed from small-scale production to assembly lines. Electricity also involved huge changes in the labor market: workers were replaced by the new technology which moreover lowered the basic skill level required for formerly skilled jobs (Lipsey et al., 2005, p.199). Thus, whereas electricity entails decreasing demand for human capital, ICT caused the opposite. Yet it was the former technology that enabled the development of the latter. When ICT arrived in the 1970s, electricity was already in its final maturity stage. As one can see from Table 1, the impact of electricity was almost continuously declining. In the last two periods of study, the effects even turned negative.

4.2 The case of general purpose technologies: ICT

To uncover the role of GPTs in economic development, the focus in the following is put on the sources of labor productivity growth related to the general purpose technology at work, ICT. As Jorgenson et al. (2007) conclude, even though aggregate data are easier to handle and to present, they might conceal considerable differences among industries. Thus, the full range of data is exploited in show-

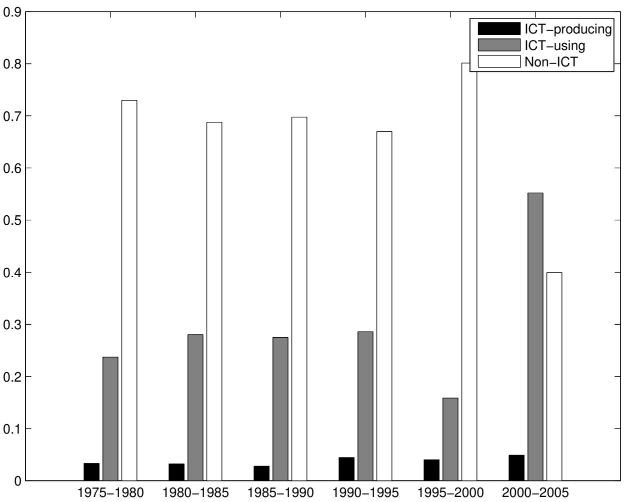

Figure 4: Sectoral contribution to annual labor productivity growth (LPG=1) in five year interval. 1975–2005

ing the spill-over effects of GPT-producing sectors for all other industries. More specifically, we seek to understand both the origins and the evolution of ICT-induced productivity growth by answering the following questions: (1) What is the impact of innovational complementarities, i.e. the impact of technical change within the ICT-sector, on the labor productivity growth in all other industries? (2) How does the utilization of ICT products affect sectoral labor productivity growth? (3) Which role can be attributed to ICT-related capital deepening? For this analysis the sectoral weights in the structural decomposition are dropped to show the impact of ICT for the different industries, regardless of their share in the net product[9]. In order to gain further insights into the relation between diffusion and productivity, a fourth dimension is introduced which shows the sectoral employment of ICT. Therefore it is necessary to cover all channels through which ICT-related products could enter the production system (presented by the transaction matrix) by incorporating imports as well as capital flows. The former makes sense, since Denmark is a net-importer of ICT products; the latter is

[9]Mathematically, this means that the numéraire is represented by a vector with all coefficients equal to one.

essential, since most products of ICT (such as computers and office machinery) are of fixed capital type and are thus not included in the intermediate demand. Hence, the compound direct requirements matrix representing both intermediate and capital demand produced domestically and abroad was used (see e.g. Lenzen, 2003) for ranking the industries according to the intensity of ICT in the respective production processes.

Since the analysis involves a time span of 42 years and 53 different industries, and the full range of data across industries is to be examined, the results are presented at a graphical level. Moreover, since the effects within the own sector are usually the strongest, the respective industry is removed from the graphs. Hence, just the inter-sectoral – and not the intrasectoral – contributions are plotted. The intensity of ICT in each sector is represented by the shades of gray of the surface: The higher the share of ICT-products, the darker the color. Industries that are displayed in black shades thus produce with the highest ICT-intensity.

Figure 5 shows the contribution of technical change *within* the ICT-industries to sectoral labor productivity growth from 1966 onwards. As Lipsey et al. (2005) point out, an important criterion for identifying a GPT is its scope of improvement. After its arrival, the crude technology takes decades to mature and show its full potential. Even though technical change in the ICT-producing sector as measured from an input-output perspective is a developable indicator for improvements of the technology itself, the results nevertheless capture the pervasive character of ICT. Thus, ICT had its strongest impact on labor productivity growth in the following manufacturing industries: Machinery and equipment, Optical and medical instruments and Transport equipment. It also significantly affected the construction sector. As regards the service sector, a high impact on Post and telecommunications, Real estate activities, Consulting activities, Research & development, Public administration and Services of membership organizations can be observed.

Furthermore, Figure 6 plots the effect of substitution for intermediate products from ICT-producing industries on the rest of the economy. Obviously, the substitution effect is highest in those sectors that adopted ICT in an early stage and use it most intensively relative to other industries: Machinery and equipment, Optical

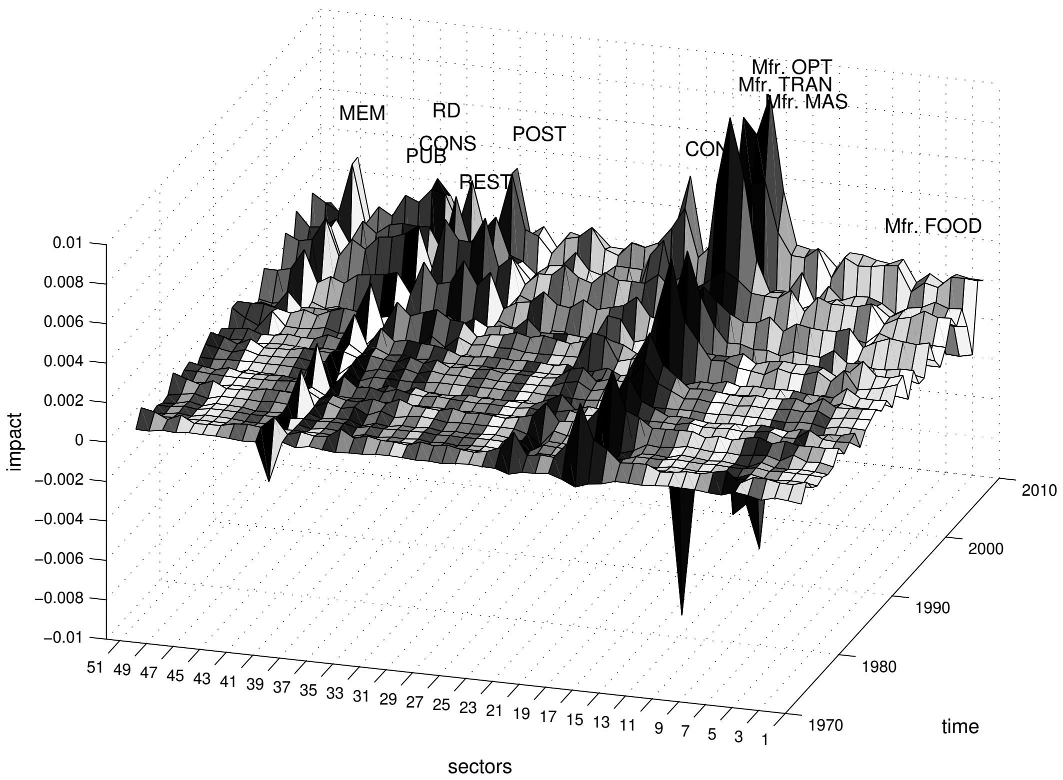

Figure 5: The contribution of technical change in the ICT manufacturing sector to sectoral labor productivity growth.
Mfr.=Manufacturing of; FOOD=Food, beverages and tobacco; MAS=Machinery and equipment n.e.c.; OPT=Optical and medical equipment; TRAN=Transport equipment; CON=Construction; POST=Post and telecommunications; REST=Real estate activities; RD=Research and development; CONS=Consultancy etc.; PUB=Public administration; MEM=Activities of membership organizations n.e.c.

and medical instruments, Transport equipment, Real estate activities, Consulting, and Public administration.

Turning to the impact of demand for ICT-capital, the pervasiveness of this GPT becomes evident once more: The increasing demand for ICT-capital has raised labor productivity growth not only in ICT-using, but also Non-ICT industries. The food manufacturing sector, for example, benefits from the capital deepening in the industries upstream (see Figure 7).

Even though the effects of technical change, the substitution effect and changes in capital demand of ICT distinguish in magnitude, the three plots share some similarities: The impact of the information and communication technology has

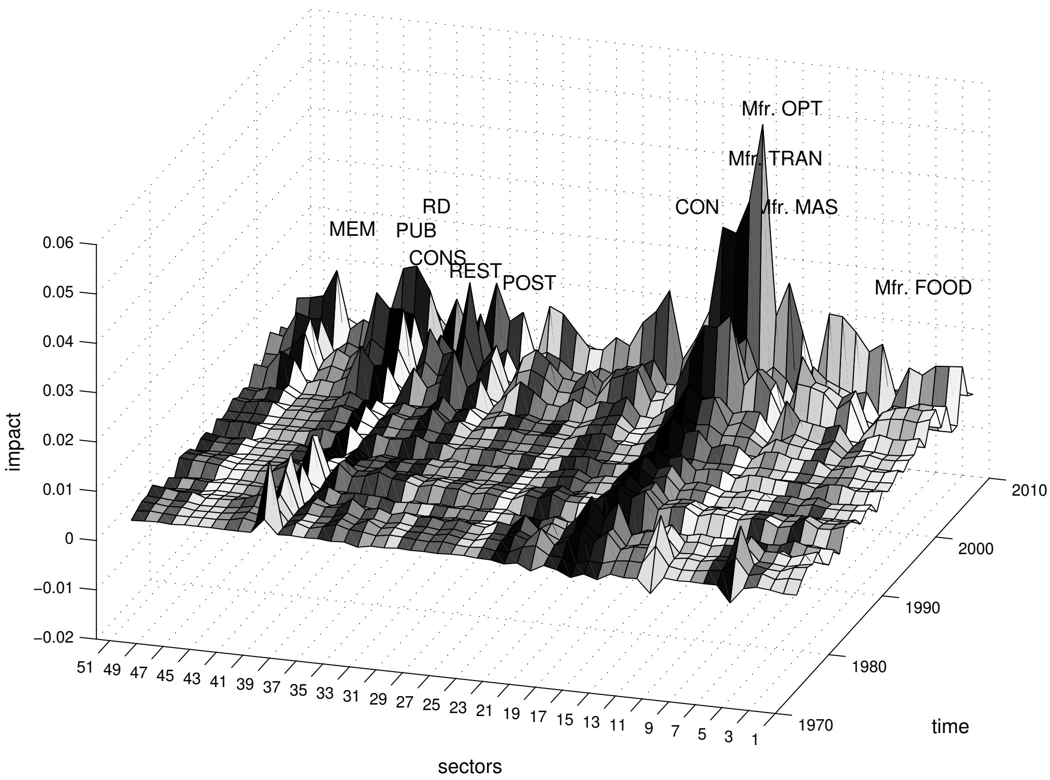

Figure 6: The contribution of factor substitution for ICT manufacturing products to sectoral labor productivity growth.

Mfr.=Manufacturing of; FOOD=Food, beverages and tobacco; MAS=Machinery and equipment n.e.c.; OPT=Optical and medical equipment; TRAN=Transport equipment; CON=Construction; POST=Post and telecommunications; RES=Real estate activities; RD=Research and Development; CONS=Consultancy etc.; PUB=Public administration; MEM=Activities of membership organizations n.e.c.

been growing over time and has spread over most of the industries. As regards the time-path, technical change in the ICT-producing industries manifests itself in labor productivity growth not earlier than from the mid 1990s onwards. Most of the important improvements in ICT, which aim at facilitating its wide-spread use, were developed between 1975 and 1990. Thus, ICT, as expected from a GPT, took longer to work through the economy. Figures 6 and 7, on the other hand, exhibit a slightly different evolution of the impact of ICT: The substitution for intermediate products and to a greater extent capital deepening unfold their effects on labor productivity growth in two waves. The first wave started in 1980 and triggered a modest rise in LPG in all industries. The second wave started at the beginning of

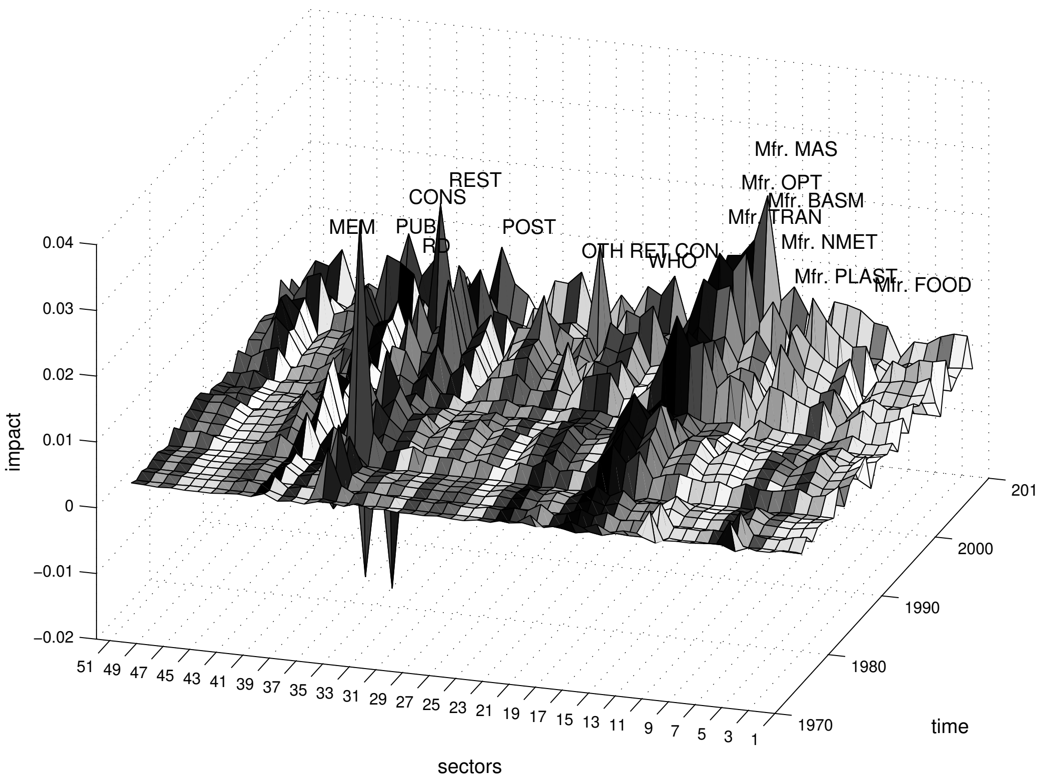

Figure 7: The contribution of capital demand for ICT manufacturing products to sectoral labor productivity growth.
Mfr.=Manufacturing of; FOOD=Food, beverages and tobacco; PLAST=Rubber and plastic products; NMET=Other non-metallic mineral products; BASM=Basic metals; MAS=Machinery and equipment n.e.c.; OPT=Optical and medical equipment; TRAN=Transport equipment; CON=Construction; WHO=Wholesale and commisson trade, exc. of m. vehicles'; OTH RET=Other retail sale, repair work; POST=Post and telecommunications; RES=Real estate activities; RD=Research and development; CONS=Consultancy etc.; PUB=Public administration; MEM=Activities of membership organizations n.e.c.

the 1990s and had a more significant impact on the economy.

The analysis of the role of ICT for labor productivity change in the rest of the economy also reveals industry clusters: The ICT sector had its strongest impact on technology-intensive manufacturing industries, such as Machinery and equipment or Transport equipment as well as on neighboring service sectors such as Post and telecommunications, Real estate and Public Administration. This supports the hypothesis that new technologies are first applied in similar industries, before they spread over more divergent sectors.

GPT diffusion and skill-induced wage dispersion

The era of ICT is also characterized by changes in the industrial organization and the institutional landscape. In this respect, one social aspect of ICT, namely its impact on skill-induced wage differentials, is discussed. As Figure 8 reveals, between 1980 and 1990 the GINI-coefficient as a measure of wage dispersion between low and high skilled labor rose sharply in the ICT-producing sectors due to the high demand of qualified workers, but decreased thereafter. Since 2000 the GINI-coefficient has been increasing again. With regard to ICT-using sectors, the GINI evolves along a similar path, though at a lower level and with an earlier peak in 1997. After 2000, the indicator decreased, but since 2003 it has shown an upward tendency again. Not surprisingly, the wage dispersion in Non-ICT-industries has declined significantly. Figure 9 links the evolution of wages of low and high skilled labor to the diffusion of ICT. A more sophisticated analysis would require econometric tools; however, as the empirical part of this paper focuses on the inter-sectoral linkages, comparing the development of ICT use among the different industries with the changes in wage dispersion of low and higher qualified workers suffices. To derive the diffusion pattern of ICT, again the compound direct requirements matrix (including imports and capital flows) is reverted to. As an indicator for dating the arrival of a GPT in a specific sector, following Jovanovic and Rousseau (2005b) the year when the new technology reaches a one per cent share in the industrial sector's stock equipment is taken. Given the compound requirements matrix and assuming regular reinvestments in ICT-capital, a coefficient above 0.01 for ICT manufacturing and ICT services indicates that the respective sector has adopted this technology. The resulting diffusion path is plotted in Figure 9, where the left ordinate presents the share of sectors that already use ICT, and the right ordinate gives the GINI coefficient as an indicator for the dispersion of wages of low and high-skilled labor. Since the ICT manufacturing sector (ICM) and computer-related service sector (ICS) follow a different time path, they are plotted separately. Figure 9 shows that office machinery has been steadily employed in over one fourth of the sectors since the 1960s, but experienced a take-off in the mid 1980s with the emergence of the new information and communication

Figure 8: Dispersion of wages of low and high-skilled labor between 1980 and 2005

technology. Another leap is observable before the dot.com-crash in 2000. As regards ICT-related services, particularly software, their diffusion follows the typical sigmoid path with a first bump in 1985 and a turning point after 1995. In the most recent years under study, both ICT manufacturing products and services have spread across the same range of sectors (about two third of all industries). Contrasting this diffusion pattern with the evolution of wage differentials, one can see that the wage dispersion peaked when the rate of adoption of ICT was about taking off in the mid 1990s. Interestingly, wage differentials between low and high-skilled labor have also increased significantly after 2000; at a time when the diffusion process had already slowed down and ICT begun to unfold its impact on labor productivity growth.

5 An evolutionary model of technological diffusion

The time path of productivity measured by the maximum real wage $\bar{w}$ in equation (3) and the respective growth rate g_t^l in definition (4) provide a suitable framework

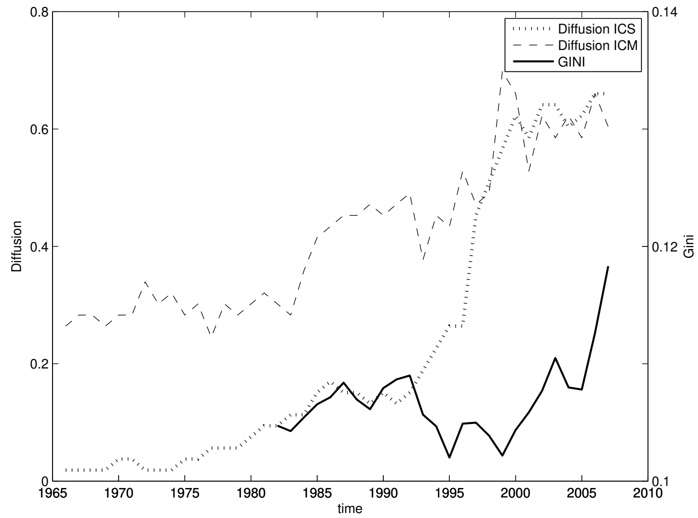

Figure 9: The diffusion of ICT manufacturing products (ICM) and ICT service products (ICS) across sectors (left ordinate) and the GINI-coefficient for low and high-skilled labor (right ordinate).

to understand the empirical results of the previous section. A thorough discussion of the underlying causes of the observed patterns is facilitated by a theoretical reconstruction of the observed data. Helpman and Trajtenberg (1996) and Aghion and Howitt (1998b) provide examples of how to explain on theoretical grounds effects of the diffusion of innovative GPTs. Both modeling approaches include R&D activities as crucial in explaining observed patterns of the diffusion process, something which induces endogeneous technical change. It is possible to provide a sound theoretical explanation of output slump and transitory wage inequality by means of an evolutionary framework based on firm growth processes. To this end, the multi-sector formalism introduced in Section 2.1 is embedded into replicator dynamic equations. Time dependency of $\bar{w}$ is therefore introduced since the technical coefficients change in time.

5.1 General model setting

The basic assumption is that for each sector n a number I_n of processes exists to produce the respective good. At time t a fraction $q_n^{i_n}(t)$ of the output of sector n

is produced by process i_n. If $a_{nm}^{i_n}$ is the input of good m and $l_{nk}^{i_n}$ the input of skill k labor to produce one unit of good n by means of process i_n, then

$$\bar{a}_{nm} = \sum_{i=1}^{I_n} q_n^{i_n} a_{nm}^{i_n} \text{ and } \bar{l}_{nm} = \sum_{i=1}^{I_n} q_n^{i_n} l_{nm}^{i_n}$$

are the respective input coefficients of the average technology defined by $\bar{A}(t)$ and $\bar{L}(t)$. In this setting, (3) can be rewritten in a time-continuous manner as

$$\bar{w}(t) = \frac{1}{\mathbf{d}^T[\mathbb{I} - \bar{A}(t)]^{-1}\bar{L}(t)\mathbf{u}}. \tag{9}$$

What remains to be answered is the time development of the market shares $q_n^{i_n}$ of the different technologies within their sector. Extra profits $\rho_n^{i_n}$ gained by some specific technology induce firm growth as follows. Assuming prices $\mathbf{p}$ to equal unit costs of production, they are implicitly given by

$$(1 + r + \rho_n^{i_n})\mathbf{p}^T\mathbf{a}_n^{i_n} + w(t)\mathbf{u}^T\mathbf{l}_n^{i_n} = p_n \tag{10}$$

with vectors $(\mathbf{a}_n^{i_n}, \mathbf{l}_n^{i_n})$ of input coefficients of technology i_n in sector n. Firm output $x_n^{i_n}$ now grows according to extra profits. Consequently,

$$\frac{\dot{x}_n^{i_n}}{x_n^{i_n}} = \rho_n^{i_n}$$

and due to $x_n^{i_n} = q_n^{i_n} x_n$ and $\dot{x}_n = \sum_{i_n=1}^{I_n} \dot{x}_n^{i_n}$ one gets $\dot{x}_n/x_n = \bar{\rho}_n$. Here x_n denotes total output of sector n, and $\bar{\rho}_n = \sum_{i=1}^{I_n} q_n^{i_n} \rho_n^{i_n}$ is the average extra profit generated in sector n. Acknowledging $\dot{x}_n^{i_n} = \dot{q}_n^{i_n} x_n + q_n^{i_n} \dot{x}_n$, the evolution of the system in the presence of technical change is described by the replicator dynamics

$$\frac{\dot{q}_n^{i_n}}{q_n^{i_n}} = \rho_n^{i_n} - \bar{\rho}_n. \tag{11}$$

A more detailed derivation and explanation of (11) is provided by Rainer (2012).

5.2 General Purpose Technology innovations: a two-sector example

The introduced evolutionary multi-sector framework can be applied to the case of GPTs as follows. Technical progress due to a new GPT implies the existence of some new kind of technical device produced by a new (basic) sector. For the case of ICTs, let sector 1 be the one producing a commodity used for reproduction and for consumption. Prior to the existence of the new GPT, the economy is described by unit production input a_{11}^1 and labor input l_{11}. As an aggregate of all consumption commodities, this sector also serves as the numéraire to express real wages w. At time $t = 0$, a new GPT is invented, leading innovating firms in sector 1 to introduce some new process characterized by

$$(1 + r + \rho_2)(a_{11}^2 + a_{12}p) + wul_{12} = 1 \tag{12}$$

with unit production input a_{11}^2 of the good itself and unit production input a_{12} of the GPT. ρ_2 denotes the extra profits gained by the new process supported by the GPT. Extra profit (respectively losses) ρ_1 of the old technology are then determined by

$$(1 + r + \rho_1)a_{11}^1 + wl_{11} = 1. \tag{13}$$

The new process needs high skilled labor remunerated by the wage premium $u > 1$. The GPT itself is produced in the new sector 2 according to

$$(1 + r)a_2 + wul_{22} = p \tag{14}$$

with capital input a_2 from the incumbent sector 1 and high skilled labor input l_{22}, yielding a price p.

Equations (11-14) determine the dynamics of the system. For the special case of $(a_{11}^1, l_{11}) = (0.3, 0.3)$ and $(a_{11}^2, a_{12}, l_{12}) = (0.4, 0.1, 0.2)$ for the incumbent and innovative process in sector $n = 1$ as well as $(a_2, l_{22}) = (0.1, 0.1)$ the diffusion process is depicted in Figures 10 and 11 qualitatively replicating the sigmoid-shaped diffusion process indicated in Figure 8. The transitional wage inequality can also be observed, which is formally derived and graphically plotted in Figure 11 based on expression (5) with

$$q_h = \frac{q\,(l_{12} + a_{12} l_{22})}{(1-q)\,l_{11} + q\,(l_{12} + a_{12} l_{22})}.$$

Also the slump after the innovation as a consequence of labor saving and capital augmenting technological progress gets apparent in Figure 10. This is an illustration of Schumpeter's *creative destruction* in a more severe manner than he imagined: the decline of the incumbent process outperforms the rise of the innvoation. As a consequence, output on average declines due to the destructive effect the innovation has on the incumbent technology.

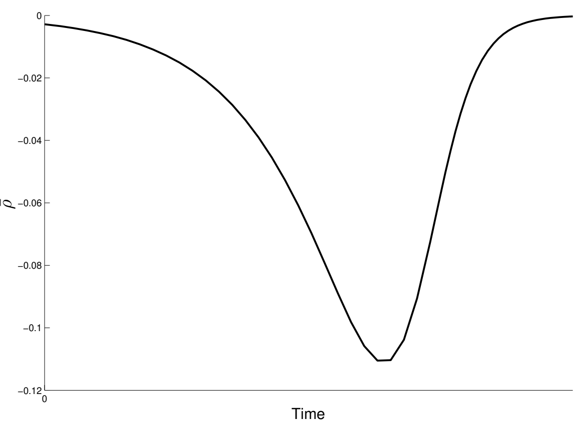

Figure 10: Negative growth in case of a GPT innovation

6 Conclusion

The economic dynamics which is triggered off by the arrival of a general purpose technology is studied on both an empirical and theoretical level.

The empirical part makes use of the Danish input-output tables that were produced at a yearly basis in order to analyze annual change in labor productivity and its sources. The time period spans from the 1960s, where the ICT revolution

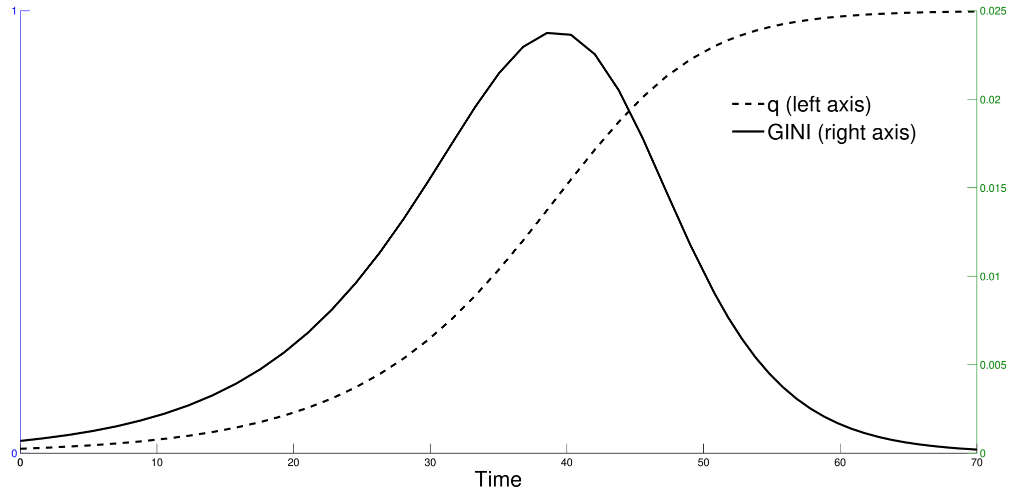

Figure 11: The diffusion of an innovative process and the resulting wage inequality.

just started, up to 2007. By accounting not only for the labor demand of a single industry, but also for the labor embodied in the upstream products, the derived labor productivity indicator gives more comprehensive insights into the impact of ICT on the economic system.

At the aggregate level, we have seen a falling trend of labor productivity particularly over the last decades. Assessing the impact on overall growth within the whole period, the ICT-producing and ICT-using industries show an increasing contribution. However, it took two decades for ICT to become a major source of productivity growth, which indicates the long time span necessary for a GPT to reach maturity and for the economic system to adapt to the new technology. Comparing ICT to another general purpose technology, namely electricity, reveals that this sector has continuously lost in importance over time. This reflects the late stage in development of this GPT.

The main purpose of the empirical part was to show that ICT was not a sectoral revolution but transformed processes throughout the whole economy: The inter-sectoral analysis demonstrates that the new information and communication technology has also affected those industries which do not produce with high ICT intensity. Furthermore, the distinction between an ICT-manufacturing and ICT-service sector allows tracking the different diffusion path of the related products. In this context, the final take-off of the ICT-manufacturing industry in the 1990ies was accompanied by a sharp rise in ICT services; this underpins the hypothesis that the diffusion of a GPT essentially depends on the development of complementary inputs that facilitate the switch from the old to the new technique. As regards the impact of ICT on the labor market, the diffusion of this technology can also be associated with transitional wage dispersion in the ICT-using industries.

Based upon this empirical evidence, ICT has been playing a crucial role in Denmark particularly in recent years, and given the current low growth rates of labor productivity, this role needs to be considered in future policy design.

As the second feature proposed by this article, the just described empirical results are reconstructed to some extent by an evolutionary multi-sectoral model. The retarded diffusion process and the induced transitional wage inequality are the two basic features which can be explained by the theoretical model. The former is a result of relative growth of innovative and non-innovative firms, and the latter is a consequence of skill premia, which are assumed to be paid for skills which are used for innovative production processes.

A

A.1 Structural decomposition analysis

Given Equation (8), the relative change in the maximum wage rate can be decomposed into four partial factors: (1) technological change (as indicated by a change in the direct input matrix A, $\Delta S \equiv S_t - S_{t-1}$), (2) change $\mathbf{\Delta l} \equiv \mathbf{l_t} - \mathbf{l_{t-1}}$ of total employment, (3) substitution effect (indicated by a change in A^T, $\Delta H \equiv H_t - H_{t-1}$) and (4) change $\mathbf{\Delta y} \equiv \mathbf{y_t} - \mathbf{y_{t-1}}$ of final demand. The result of each decomposition is an N-dimensional vector that shows the contribution of the respective determinant to sectoral labor productivity growth:

$$SS_{t-1} \equiv -\mathbf{d}^T \left[\Delta S \; \hat{\mathbf{l}}_{t-1} \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{15a}$$

$$ll_{t-1} \equiv -\mathbf{d}^T \left[S_t \; \Delta\hat{\mathbf{l}} \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{15b}$$

$$LL_{t-1} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1}[\text{diag} \; (\Delta H \; \mathbf{y}_{t-1})] \; \hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t \; \mathbf{e} \tag{15c}$$

$$YY_{t-1} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1}[\text{diag} \; (H_t \; \Delta\mathbf{y})]\hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t\mathbf{e} \tag{15d}$$

Depending on data availability, the labor input is further decomposed into low-skilled (l^1) and higher-skilled (l^2) labor (hours per unit of output).

$$ll^1_{t-1} \equiv -\mathbf{d}^T \left[S_t \; \Delta\hat{\mathbf{l}}^1 \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{16a}$$

$$ll^2_{t-1} \equiv -\mathbf{d}^T \left[S_t \; \Delta\hat{\mathbf{l}}^2 \; [\text{diag} \; (H_{t-1} \; \mathbf{y}_{t-1})]^{-1}\right] \; w_t \; \mathbf{e} \tag{16b}$$

Equations (16a-16b) replace (15c) for the time span of 1980 to 2005. Furthermore, final demand is decomposed into ICT-related and Non-ICT investments:

$$YY^{ICT}_{t-1} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1}[\text{diag} \; (H_t \; \Delta\mathbf{y}^{ICT})]\hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t\mathbf{e} \tag{17a}$$

$$YY^{NonICT}_{t-1} \equiv \mathbf{d}^T \left[S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1}[\text{diag} \; (H_t \; \Delta\mathbf{y}^{Non-ICT})]\hat{\mathbf{x}}_{t-1}^{-1}\right] \; w_t\mathbf{e} \tag{17b}$$

Equations (17a) and (17b) sum up to (15d).

Definitions (15a-15d) reveal an obvious index problem that affects precision and interpretation of the outcome whenever the number of partial factors exceeds two. So far all variables are weighted by $t-1$ values. However, in the case of four determinants we have 4! possible decompositions for each factor, resulting from the permutation of the variables with respect to time. Dietzenbacher and Los (1998) showed that the polar decomposition gets remarkably close to the average of all possible decompositions; thus it suffices to calculate the second polar decomposition, by starting with the values in period t instead of period $t-1$

and taking the average of the two:

$$SS_t \equiv -\mathbf{d}^T \left[\Delta S \hat{\mathbf{l}}_t \, [\mathrm{diag}(H_t \mathbf{y}_t)]^{-1}\right] w_t \; \mathbf{e} \tag{18a}$$

$$ll_t \equiv -\mathbf{d}^T \left[S_{t-1} \; \Delta\hat{\mathbf{l}} \; [\mathrm{diag} \; (H_t \; \mathbf{y}_t)]^{-1}\right] w_t \; \mathbf{e} \tag{18b}$$

$$LL_t \equiv \mathbf{d}^T \left[S_{t-1} \; \hat{\mathbf{l}}_{t-1} \; \hat{\mathbf{x}}_{t-1}^{-1} \; [\mathrm{diag} \; (\Delta H \; \mathbf{y}_t)\right] \hat{\mathbf{x}}_t^{-1}] \; w_t \; \mathbf{e} \tag{18c}$$

$$YY_t \equiv \mathbf{d}^T \left[S_{t-1} \; \hat{\mathbf{l}}_{t-1} \; \hat{\mathbf{x}}_{t-1}^{-1} [\mathrm{diag} \; (H_{t-1} \; \Delta\mathbf{y})\right] \hat{\mathbf{x}}_t^{-1}] \; w_t \; \mathbf{e} \tag{18d}$$

Hence, the initial decomposition of the labor productivity growth indicator[10] reads as follows:

$$\begin{aligned} g_t^l = \frac{1}{2}\mathbf{d}^T \; \big[\{(LL_{t-1} + LL_t\} + \{YY_{t-1} + YY_t\} + \\ \{SS_{t-1} + SS_t\} + \{ll_{t-1} + ll_t\} \big] \; w_t \; \mathbf{e} \end{aligned} \tag{19}$$

Inner- and intersectoral linkages

To show the impact of ICT on productivity changes across industries the direct input matrices A and A^T are decomposed into their submatrices. Following Miller and Blair (2009, pp.603-605), changes in S and H are related to changes in the underlying direct input matrices:

Proposition 1. *Changes ΔA of the input matrix A translate into changes ΔH of the Leontief Inverse and changes ΔS of the Sraffa Inverse according to*

$$\Delta S = S_{t-1} \; \Delta A \; S_t \quad \text{and} \tag{20a}$$

$$\Delta H = H_{t-1} \; \Delta A^T H_t. \tag{20b}$$

Proof. (20b) is the transpose of (20a). Thus one only has to show that

$$(\mathbb{I} - A_t)^{-1} - (\mathbb{I} - A_{t-1})^{-1} = (\mathbb{I} - A_{t-1})^{-1}(A_t - A_{t-1})(\mathbb{I} - A_t)^{-1}.$$

[10] For equations (15c) and (15d) as well as for equations (18c) and (18d), note that $\hat{\mathbf{x}}_{t-1}^{-1}\Delta\hat{\mathbf{x}}\hat{\mathbf{x}}_t^{-1} = \hat{\mathbf{x}}_t^{-1}\Delta\hat{\mathbf{x}}\hat{\mathbf{x}}_{t-1}^{-1} = -\Delta(\hat{\mathbf{x}}^{-1}) \equiv \hat{\mathbf{x}}_{t-1}^{-1} - \hat{\mathbf{x}}_t^{-1}$.

But this can be shown to be true by post-multiplication with $(\mathbb{I} - A_t)$ and pre-multiplication with $(\mathbb{I} - A_{t-1})$. $\square$

Analyzing the impact of a specific sector on all other sectors necessitates to take a closer look onto the economic structure. To assess how sectors are linked together, the direct input matrix A is split up in such a way that each row composes an own submatrix. By doing so, the isolated effect of one sector on the production technique can be traced back. Decomposing A into individual sectors means to create submatrices such that $\Delta A = \sum_{i=1}^{N} \Delta A^{(i)}$ with

$$\Delta A^{(i)} \equiv \begin{pmatrix} 0 & \dots & 0 & \dots & 0 \\ \vdots & & \vdots & & \vdots \\ \Delta a_{i1} & \dots & \Delta a_{ij} & \dots & \Delta a_{in} \\ \vdots & & \vdots & & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{pmatrix}.$$

By recalling Proposition 1 and introducing $\Delta A^{(i)}$ into equations (15a) and (18a), the effect of changes in the production process of a specific sector due to, for instance, technical change on labor productivity growth in all other sectors can be analyzed:

$$SS_t \equiv -\mathbf{d}^T \left[S_t \; \Delta A \; S_{t-1} \; \hat{\mathbf{l}}_t \; \text{diag}(H_t \mathbf{y}_t)^{-1} \right] w_t \; \mathbf{e}$$

Applying the same procedure to equations (15c) and (18c) allows tracking the effect of changes in demand for a specific factor, i.e. the effect of substituting one input for another:

$$LL_t = \mathbf{d}^T \left[S_{t-1} \; \hat{\mathbf{l}}_{t-1} \; \hat{\mathbf{x}}_{t-1}^{-1} \; [\text{diag} \; (H_t \; \Delta A^T \; H_{t-1} \; \mathbf{y}_t)] \; \hat{\mathbf{x}}_t^{-1} \right] \; w_t \; \mathbf{e}$$

Finally, the role of fixed capital provided by the ICT-sector is scrutinized. There is a bunch of studies discussing the importance of the ICT-capital producing industries for ICT-capital-using sectors (see e.g. Jorgenson et al., 2007). It is obvious that a big part of the output of the ICT industry represents assets that remain longer than a year in the production process. These assets are therefore not captured within the direct input matrix, but are declared in the investment demand of an input-output table, so that for a comprehensive analysis changes in ICT-capital have to be taken into account in one way or the other. One possible approach is to re-weight the direct input-matrix by the share of fixed capital used in the production process. This implies the need for the so-called centre-coefficients for each sector, where the production recipe also represents capital assets and thus needs to be related to rates of profit. Another more simplistic approach that implies the incorporation of investment flows into the previous analysis is taken in this article to facilitate the empirical analysis: The final demand vector $\mathbf{y}$ is disentangled into different categories; furthermore the column of investment demand is replaced by the respective investment matrix Y_{inv}, which shows (similar to the industrial transaction matrix) the inner- and inter-sectoral deliveries of capital assets:

$$YY_{t-1} = \mathbf{d}^T \; [S_t \; \hat{\mathbf{l}}_t \; \hat{\mathbf{x}}_t^{-1} \; [\text{diag} \; (H_t \; \Delta(Y_{\text{inv}}\mathbf{e} + \mathbf{y}_{\text{rest}}))] \; \hat{\mathbf{x}}_{t-1}^{-1}] \; w_t \mathbf{e}$$

A.2 Industry classification

Table 2: Aggregation of Danish industries. Note: The numbers in the second column indicate the assignment of the respective sector to the Danish 130-industry-classification, the third column to ICT-producing, ICT-using and Non-ICT industries.

Code	Industry	Aggregation	ICT-classification
1	Agriculture	1	Non-ICT
2	Horticulture, orchards etc.	2	Non-ICT
3	Agricultural services; landscape gardeners etc.	3	Non-ICT
4	Forestry	4	Non-ICT
5	Fishing	5	Non-ICT
6	Extr. of crude petroleum, natural gas etc.	6	Non-ICT
7	Extr. of gravel, clay, stone and salt etc.	7	Non-ICT
8	Mfr. of food, beverages and tobacco	8-18	Non-ICT
9	Mfr. of textiles, wearing apparel, leather	19-21	Non-ICT
10	Mfr. of wood and wood products	22	Non-ICT
11	Mfr. of paper prod.; printing and publish.	23-26	Non-ICT
12	Mfr. of refined petroleum products etc.	27	Non-ICT
13	Mfr. of chemicals and man-made fibres etc.	28-35	Non-ICT

Continued on next page

Table 2 – continued from previous page

Code	Industry	Aggregation	ICT-classification
14	Mfr. of rubber and plastic products	36-38	Non-ICT
15	Mfr. of other non-metallic mineral products	39-41	Non-ICT
16	Mfr. and processing of basic metals	42-47	Non-ICT
17	Mfr. of machinery and equipment n.e.c.	48-52	ICT-using
18	Mfr. of ICT equipment	53-55	ICT-producing
19	Mfr. of optical and medical equipment	56	ICT-using
20	Mfr. of transport equipment	57-59	ICT-using
21	Mfr. of furniture; manufacturing n.e.c.	60-62	Non-ICT
22	Electricity supply	63	Non-ICT
23	Gas and water supply	64-66	Non-ICT
24	Construction	67-70	Non-ICT
25	Sale and repair of motor vehicles etc.	71-73	ICT-using
26	Ws. and commis. trade, exc. of m. vehicles	74	ICT-using
27	Retail trade of food etc.	75	ICT-using
28	Department stores	76	ICT-using
29	Re. sale of phar. goods, cosmetic art. etc.	77	ICT-using
30	Re. sale of clothing, footwear etc.	78	ICT-using
31	Other retail sale, repair work	79	ICT-using
32	Hotels and restaurants	80-81	Non-ICT
33	Land transport; transport via pipelines	82-85	Non-ICT
34	Water transport	86	Non-ICT
35	Air transport	87	Non-ICT
36	Support. trans. activities; travel agencies	88-89	Non-ICT
37	Post and telecommunications	90	ICT-using
38	Financial intermediation	91-92	ICT-using
39	Insurance and pension funding	93-94	ICT-using
40	Activities auxiliary to finan. intermediat.	95	ICT-using
41	Real estate activities	96-98	ICT-using
42	Renting of machinery and equipment etc.	99	ICT-using
43	Computer and related activities	100-101	ICT-producing
44	Research and development	102-103	ICT-using
45	Consultancy etc. and cleaning activities	104-109	ICT-using
46	Public administration etc.	110-113	Non-ICT
47	Education	114-118	Non-ICT
48	Health care services	119-120	Non-ICT
49	Social institutions	121-122	Non-ICT
50	Sewage and refuse disp. and similar act.	123-125	Non-ICT
51	Activities of membership organiza. n.e.c.	126	ICT-using
52	Recreational, cultural, sporting activities	127-128	Non-ICT
53	Other service activities	129-130	ICT-using

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