ICT, Firm Growth and Productivity

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Abstract

In this paper, we use a rich dataset providing detailed information about spending in various components of ICT (hardware, communication equipment and software) to analyse the consequences of ICT investment on firm growth and firm productivity. We find strong evidence that all three components of ICT spending at the firm level correlate strongly with firm growth and productivity, although firm selection appears to play an important role to explain this relationship.

1 Introduction

Recent advancement in information and communication technologies (ICT) have led to a profound transformation of the way firms operate. By improving access to information and promoting smoother communication, it eases coordination of activities within the firm and with suppliers and customers. These improvements should translate into productivity gains, although we are still missing strong evidence about this link, especially outside of the US.

In this paper, we use recently released rich datasets from Statistics Denmark to investigate how various measures of ICT spending correlate with firm growth and productivity. We match firm level accounting statistics for the population of Danish firms with 12 years of survey on IT spending to provide a thorough examination of these links using a well accepted econometric framework

We start by studying the relationship between firm growth and ICT investment. Firm growth, also referred to as employment growth, is considered as a standard measure of performance, and firms investing in better technologies are also more likely to grow. Alternatively, more advanced technologies might also imply that firms require less workers in the production process, so the relationship could go both ways.

We next analyze the relationship between total factor productivity and ICT. We consider various approaches. First, we compute a 3-factor (labor, material and capital) total factor

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productivity measure following the approach discussed among others in Syverson (2011). The standard procedure is then to correlate our measures of TFP correlates with the various ICT use variables. As a second approach, we estimate a 3-factor production function where ICT enters directly in our estimation inside the law of motion of productivity, as recommended in other contexts by Doraszelski and Jamandreu (2013) and De Loecker (2013). Our last measure considers 4 factors of production as we distinguish between ICT capital and other types of capital. The aim of this analysis is to analyze the relative contribution to output of the various inputs with a focus on ICT capital.

Our results are in line with our expectations. We find that measures of IT spending are strongly related to firm growth and productivity. Software and hardware spending are positively related to firm employment growth in our preferred specification that controls for time invariant firm characteristics. Similarly, all three measures of ICT spending correlate with total factor productivity in a simple OLS setting, although the evidence is less convincing with a fixed effect analysis. Finally, our 4-factor production function estimation provides evidence of a large contribution of ICT capital to output.

There have been many papers in the literature addressing this question, usually with smaller datasets and less structural approach to deal with the endogeneity (see Munch et al., 2018 for a recent survey of the literature). Brynjolfsson and Hitt (2003) and Dhyne et al. (2017) are probably the closest papers to ours. The first paper uses a small sample of US firms over a 8-year and relate changes in computer capital to differences in total factor productivity growth. They find that IT capital makes a significant contribution to productivity and output growth in the short run and in the long run. The second paper follows a similar approach but uses a novel measure of IT, as the purchases from firms in the IT sector. They find large marginal returns of IT capital across industries.

A recent paper by Kroman and Sørensen (2017) uses a similar approach but with different motivation and methodology. They are mostly interested in the effect of automation on productivity. For this purpose, they run a survey on automation for 567 Danish manufacturing firms in order to collect new measures of ICT use in production run in 2012, asking retrospective questions for the years 2005, 2007 and 2010. They are able to generate precise measures of automation such as the share of new investment in machinery and equipment targeted for automation; subjective questions about the extent of mechanization and automation of the production process at various stages; and subjective questions about the evolution of various measures of performance related to the production process itself (run time, setup time, quantity produced per worker, etc…). This survey is then merged with other datasets to estimate the relationship between automation and productivity. They distinguish between three types of capital and build an automation index based on the answers to 8 specific questions on automation scope. They find that their index of automation is highly related to value added, and their measures of IT and automated capital positively contributes to output.

We differ from the above paper in three important dimensions. First, we provide a robust econometric framework that deals with the basic endogeneity problem faces in estimating production function by adopting the modified control function approach, as advocated by Olley and Pakes, Levinsohn and Petrin, and then modified by Wooldridge and Ackerberg, Caves and Frazer. Second, we disentangle ICT investment into three subcomponents (hardware, software and communication equipment) to analyze their respective effects on firm growth and productivity, instead of relying on a single ICT measure. Third, we extend the period of analysis to 2000-2015 and to the entire set of firms considered in the ICT surveys run by Statistics Denmark. By considering a larger sample of firms and a longer time span, we capture more heterogeneity in investment behavior in both the cross section and time dimensions, and are able to implement clean econometric methods. One drawback compared to Kroman and Sørensen (2017) is that we have no information on management quality nor on automation. However, we see our analysis as complementary to theirs, as we are able to capture the time dimension and analyze a variety of ICT measures collected by Statistics Denmark.

Section 2 describes the datasets that we use and provides basic summary statistics. In section 3, we explain the different elements of our empirical investigation. Subsection 3.1 addresses the industry level analysis on the relationship between ICT investment and ICT capital intensity. Subsection 3.2 focuses on the firm level relationship between firm growth and ICT investment. Subsection 3.3 describes the various approaches to measure firm productivity and its relationship to ICT investment. The results are presented in section 4 and section 5 concludes and suggests extensions to our current framework.

2 Data

Our empirical approach makes use of several rich datasets provided by Statistics Denmark. The first one provides the basic variables needed for the computation of firm growth and TFP, and the estimation of production functions. The Accounting Statistics (Regnskabsstatistikken) cover the population of Danish firms for a long period of time and contains among other variables measures of revenue, cost of materials, number of full time employees (FTEs), various measures of capital and investment. It also contains the date where the firm was founded, and when it went bankrupt when it occurred. We only consider firms with at least one employee. Statistics Denmark devoted a considerable effort to map firms to the revised industrial statistical nomenclature (NACE Rev 2) back until 2000.

Aggregate figures about the composition of capital are provided by the EU KLEMS project. Capital stock is divided into several components, including three components of ICT capital: software and databases, hardware and communication equipment. Figure 1 shows the shares of these three components in total real capital for the market economy in Denmark. As we can see, they have been rising over time, especially the hardware and software components.

Figure 1: Shares of ICT components in total capital (Denmark)

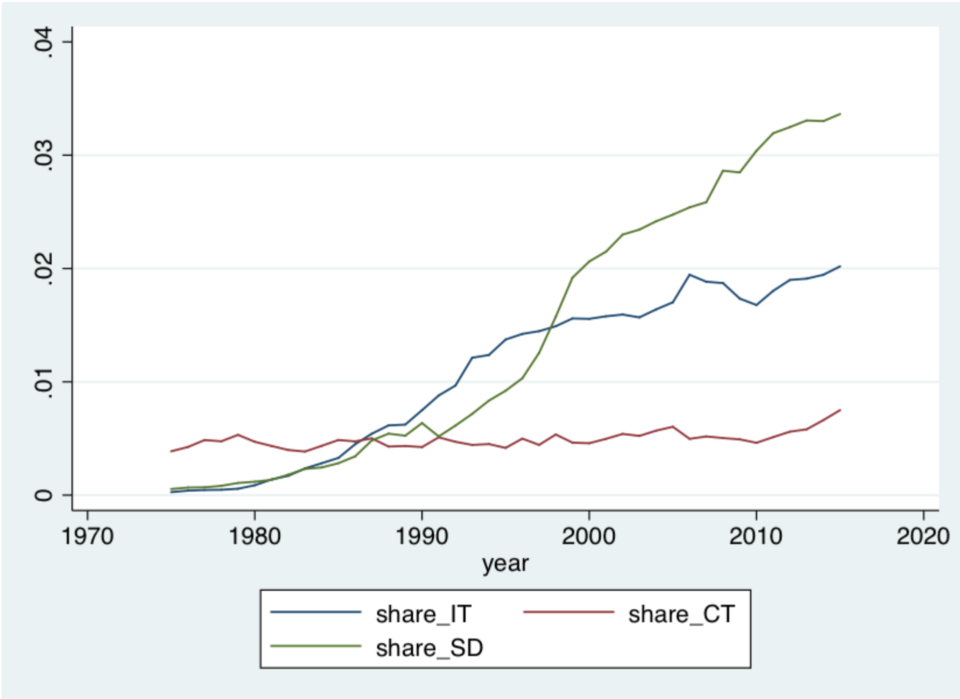

Figure 2: Shares of ICT components in total capital (US)

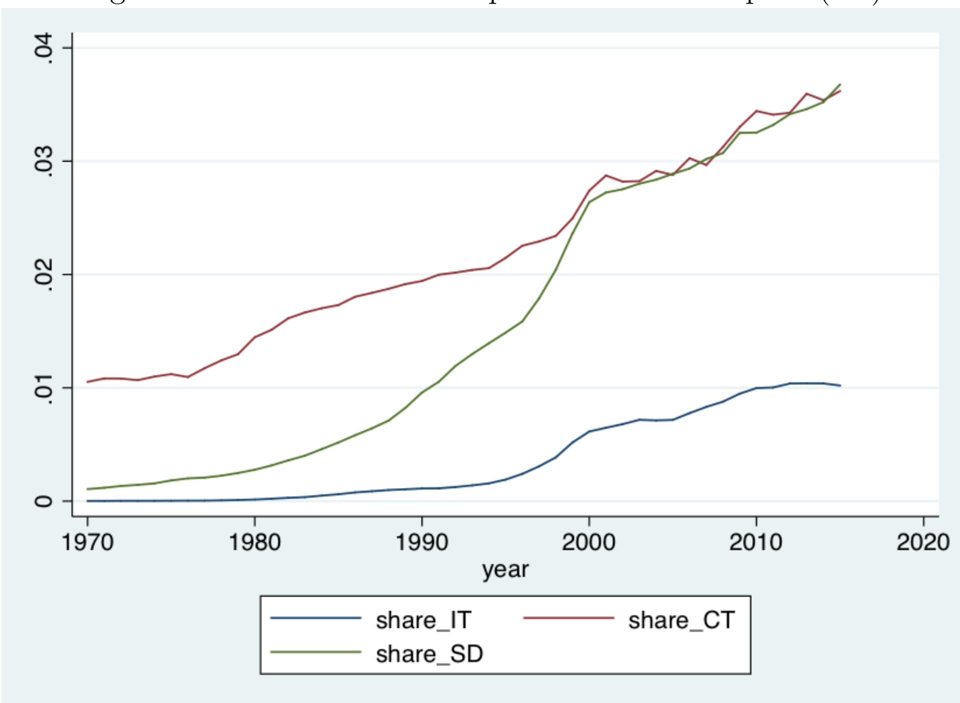

Figure 3: Average real spending by type of ICT capital (in thousands DKK)

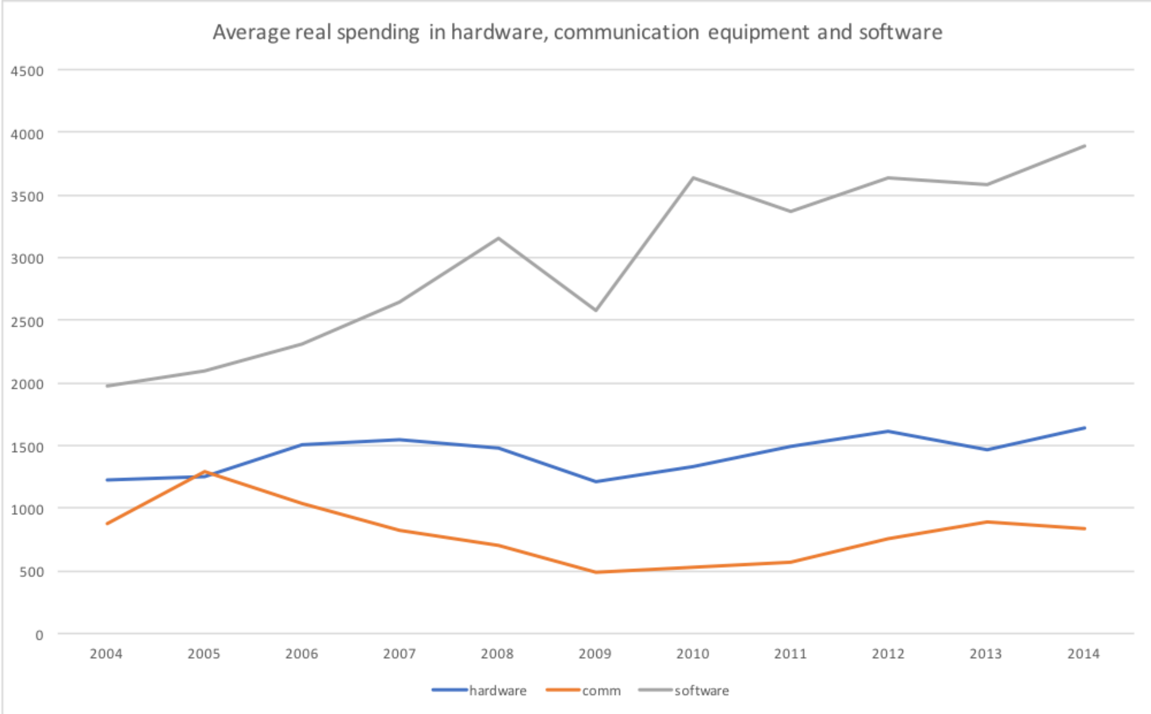

Figure 2 shows the same graph for the US.[1] One clear difference between the two countries is the share in telecommunication equipment capital. In the US, it increased a lot in a gradual way since the end of the 1970s. In Denmark, it has remained relatively flat. The evolution of the share of software and database capital is quite similar otherwise, while Denmark appears to have invested a higher share in hardware.

At the firm level, we also make use of survey run by Statistics Denmark about firm spending in IT (VITU). That survey was started in 2004 and was intended to provide a monetary value to firms' investment in ICT. Firms are asked to provide the amount invested in hardware, software and communication equipment. They are also asked about internal development of software. Firms are instructed in the questionnaire about which items fall in each category.[2] In particular, it captures relatively standard items such as computers or networks, and does not include more recent advances in technology such as machine learning and the internet of things. Every year, around 3,000 firms answered to the survey.

Figure 3 shows the average spending in all three components. Not surprisingly, the evolution is consistent with the aggregate picture from figure 1. The average spending has increased a lot in software, but has remained stable in hardware, and has declined relatively for communication equipment.

[1] Appendix A shows similar figures for Finland, Germany and Sweden, although the data is only available from the mid 1990's for the last two countries.

[2] See this link on Statistics Denmark website for more information about the survey and the sampling strategy: https://www.dst.dk/en/Statistik/dokumentation/documentationofstatistics/ict-expenditure-in-enterprises

3 Empirical Framework

3.1 Firm growth and ICT use

Firm growth is computed as the growth of employment from $t-1$ to t, as popularized by Davis and Haltiwanger (1992). The advantage of this measure is that it is simple to compute and bounded between -2 and 2, where it is associated respectively with an exit or an entry.[3]

$$g_{it} = \frac{L_{it} - L_{i(t-1)}}{(L_i t + L_{i(t-1)})/2}$$

Once this measure is computed from the data, we can use it a measure of performance and analyze how it is affected by ICT measures at the firm level. The regression that we run is therefore:

$$g_{it} = f(ICT_{i(t-1)}, X_{it}) + \epsilon_i t$$

where Xit is a vector of control variables at the firm level.

3.2 Productivity and ICT use

3.2.1 3 factor production function

A starting point in the analysis is to consider investment in ICT or measures of ICT use not as inputs, but as decisions affecting firms' efficiency in the law of motion of productivity. This is what Brynjolfsson and Hitt (2003) refer to as the 3-factor production function approach.

Productivity can easily be computed, following a similar logic to growth accounting, using the so called cost based approach (see e.g. Syverson, 2011 for a discussion). The computed total factor productivity (TFP^C) will simply be defined as:

$$TFP^C_{it} = logQ_{it} - \alpha^M_{jt} logM_{it} - \alpha^L_{jt} logL_{it} - \alpha^K_{jt} logK_{it}$$

where i is a firm index, t is a time index, Q is deflated revenue, M is deflated material, L represents the number of workers and K is capital, defined following the perpetual inventory method. The alphas represent the cost share of each input at the industry level and are provided by the EU KLEMS dataset.

Another standard way to obtain a measure of TFP is to estimate the production function. We simply regress the log of real output over the log of real material, labor and real total capital. Once we obtain the coefficients of the input variables, we can simply retrieve productivity as the error term from the regression.

$$logQ_{it} = \beta^M_j logM_{it} + \beta^L_j logL_{it} + \beta^K_j logK_{it} + \epsilon_{it}$$

[3]These firm level growth rates can then be aggregated at the economy level or sector level to compute job creation and job destruction rates.

The error term is further decomposed in two components $\varepsilon_t = \omega_t + \eta_t$. η_t is a standard measurement error or and ω_t is the technical efficiency shock. We refer further to ω as the TFP estimated (TFP^E_{it}).

A well known problem in this literature is that the choice of inputs is potentially correlated with the error term if the manager can observe the level of productivity. Various techniques have been developed to deal with this problem. We will adopt the popular control function approach, as first advocated by Olley and Pakes (1996) and refined over the years. Appendix B describes the estimation algorithm based on Wooldridge (2009).

The various measures of TFP obtained are then related to our ICT measures, as described in subsection 3.2:

$$TFP_it = f(ICT_i(t-1), X_it) + \epsilon_it$$

3.2.2 4 factor production function

Another popular approach is to split firms' capital stock into an ICT component and a non ICT component, and consider both as separate inputs. The problem of this approach is that we do not have a measure of ICT capital stock, but only of investment flows. The traditional way to deal with this problem is to infer the share of ICT capital in total capital based on the observed flows. This is obviously a proxy and might involve significant additional measurement error, on top of the well known difficulty to measure capital in the first place (see e.g. the discussion in Collard Wrexler and De Loecker, 2016).

The way to compute the initial stock of IT capital is the following: look at investments flows in ICT for a given initial period, say 4 years, then look at the average share of ICT flows relative to total investments. Use this average share to compute the initial share of ICT capital by multiplying the measure of initial capital stock for the first year where the firm is observed with the share. We obtain a measure of initial non ICT capital by subtracting ICT capital from total capital. Then allow both types of capital to depreciate according to their own rates, and add real investment deflated by their own deflators (see Appendix A.2 in Konings et al., 2017 for a more complete discussion).

The analysis then proceeds as in the 3-input case, but with one additional variable and another parameter to estimate. In this context, our interest is to evaluate the impact of ICT capital on output.

4 Results

4.1 Firm growth, productivity and ICT spending

Results from table 1 show that software and hardware spending are strongly and positively related to employment growth once controlling for firm fixed effect. Looking at the effect of the control variables, larger firms also appear to grow at a lower rate, while capital intensive firms are growing at a higher rate.

Table 1: Firm growth and ICT investments

	(1)	(2)	(3)	(4)
Dep. var.:		g		
log (software spending) in $t-1$	-0.001	0.005***	0.001	0.004**
	[0.001]	[0.002]	[0.002]	[0.002]
log (communication spending) in $t-1$	0.007***	0.002	0.007***	0.003
	[0.001]	[0.002]	[0.002]	[0.002]
log (hardware spending) in $t-1$	0.024***	0.023***	0.020***	0.024***
	[0.002]	[0.002]	[0.003]	[0.003]
Share of software spending in $t-1$			0.000	0.000
			[0.000]	[0.000]
Share of communication spending in $t-1$			0.012	-0.015
			[0.024]	[0.033]
Share of hardware spending in $t-1$			0.040***	-0.019
			[0.015]	[0.020]
log(employment) in $t-1$	-0.044***	-0.242***	-0.041***	-0.238***
	[0.002]	[0.008]	[0.002]	[0.008]
log (capital per worker) in $t-1$	0.010***	0.068***	0.011***	0.069***
	[0.002]	[0.006]	[0.002]	[0.006]
constant	-0.089***	0.028	-0.113***	0.001
	[0.028]	[0.097]	[0.029]	[0.098]
Year dummies		YES		
Industry fixed effect		YES		
Firm fixed effect	NO	YES	NO	YES
N	14163	14163	14013	14013
R^2	0.081	0.664	0.079	0.663

Standard errors in brackets

* p<0.10, ** p<0.05, *** p<0.01

As a next step, we use our accounting dataset to compute and estimate total factor productivity using three inputs, as explained in section 3. The estimation is done separately for each 2-digit industry. Table 2 shows how our measures of TFP correlate with past investment in software, communication equipment and hardware. In the simple OLS case, all three measures are strongly related to TFP, with hardware appearing to have the strongest effect. Once we use a fixed effect, however, only the spending in communication equipment shows a significant effect in the case of the estimated productivity, and a negative effect of software spending in the case of computed productivity. This might suggest a strong selection effect or more generally little variation over time in the spending heterogeneity across firms.

Table 2: ICT investment and productivity

	(1)	(2)	(3)	(4)
	TFP^C		TFP^E	
log (software spending) in $t-1$	0.009**	-0.014**	-0.001	-0.001
	[0.004]	[0.006]	[0.002]	[0.008]
log (communication spending) in $t-1$	0.014***	0.008	0.016***	0.025***
	[0.005]	[0.006]	[0.003]	[0.008]
log (hardware spending) in $t-1$	0.041***	0.011	0.020***	-0.005
	[0.006]	[0.007]	[0.003]	[0.011]
Firm fixed effect	NO	YES	NO	YES
N	12,769	12,769	12,099	12,099
R^2	0.839	0.946	0.989	0.975

Standard errors in brackets

* p<0.10, ** p<0.05, *** p<0.01

All specifications include year and industry dummies, lagged firm size and lagged capital intensity

A cleaner way to proceed is to estimate the effect of ICT components directly in the law of motion of productivity, as advocated by De Loecker (2013) and Doraszelski and Jamandreu (2013). One problem is that the estimation can then only be run for the surveyed firms, and this restricts the sample size. What most researchers are doing is to estimate the production function at a more aggregate level, i.e. using all firms in manufacturing and all firms in services, instead of running the estimation by 2-digit industry. We follow a similar approach. Table 3 shows the results. All three components are strongly related to productivity in a significant way, although hardware appears to have the stronger effect. We also notice that the contribution of ICT to productivity appears to be stronger in services than in manufacturing.

Table 3: ICT investment and productivity

	Manufacturing TFP^E	Services TFP^E
log (software spending) in $t-1$	0.006*	0.027***
	[0.004]	[0.004]
log (communication spending) in $t-1$	0.008**	0.026***
	[0.004]	[0.005]
log (hardware spending) in $t-1$	0.028***	0.060***
	[0.005]	[0.006]
N	3,165	6,942

Standard errors in brackets
* p<0.10, ** p<0.05, *** p<0.01

Table 4 shows the coefficients of the 4-input specification where capital is split into an ICT and a non-ICT component. The regression is run separately for manufacturing and service firms. We use two different specifications: OLS Cobb Douglas and WLP Cobb Douglas. Both specifications show that ICT capital contributes significantly to output. Our coefficients in the WLP Cobb Douglas are extremely similar to those obtained by Konings et al. (2017) for Belgium, using different measurement of ICT investment. The coefficients are also similar between the manufacturing and the service industries. The coefficients of both types of capital increase when we control for endogeneity in the WLP specification, as is commonly observed in the literature.

Table 4: ICT investment and productivity

	Manufacturing		Services	
	OLS CD	WLP CD	OLS CD	WLP CD
$logM$	0.462*** (0.008)	0.531*** (0.009)	0.254*** (0.004)	0.280*** (0.006)
$logL$	0.494*** (0.013)	0.395*** (0.015)	0.646*** (0.012)	0.591*** (0.014)
$logKIT$	0.043*** (0.004)	0.105*** (0.023)	0.031*** (0.005)	0.107*** (0.024)
$logKNIT$	0.050*** (0.005)	0.071*** (0.011)	0.070*** (0.005)	0.086*** (0.012)
# obs.	2,231	1,908	3,111	2,454

5 Conclusion

In this paper, we used a rich dataset providing detailed information about spending in various components of ICT (hardware, communication equipment and software) to analyse the consequences of ICT investment on firm growth and firm productivity. We found strong evidence that all three components of ICT spending at the firm level correlate strongly with firm growth and productivity, although firm selection appears to play an important role to explain this relationship.

Our understanding of the relationship between ICT and productivity is still very incomplete, but we believe our analysis and the richness of our datasets open the door to future research projects. In particular, we would like to investigate the complementarity between ICT investment and organizational change, the relationship between ICT and workforce composition, and the link with offshoring and R&D.

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A Share of ICT components

Figure 4: Shares of ICT components in total capital (Finland)

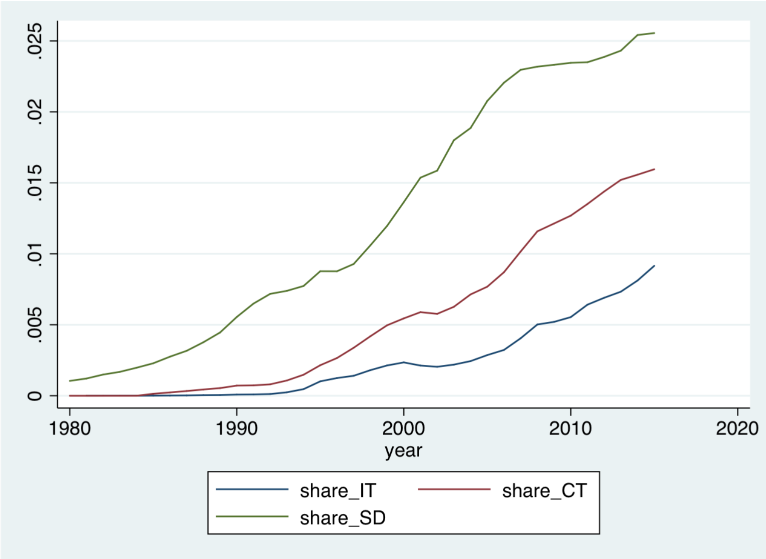


Figure 5: Shares of ICT components in total capital (Germany)

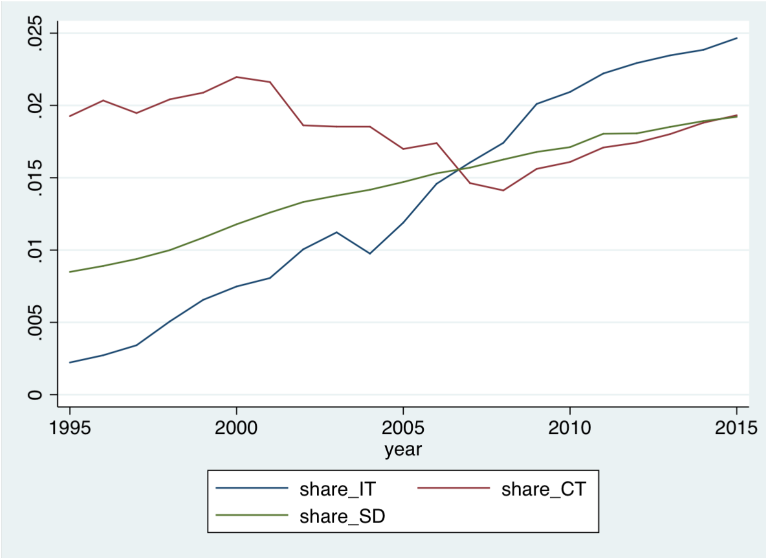
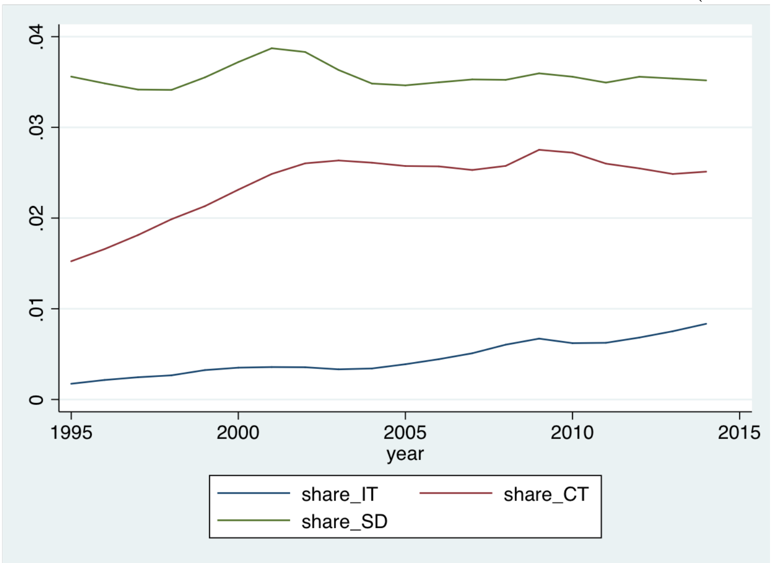


Figure 6: Shares of ICT components in total capital (Sweden)



B Estimation algorithm

We estimate the following production function:

$$q_t = \beta_l l_t + \beta_m m_t + +\beta_k k_t \epsilon_t \tag{1}$$

where q_t is the log of deflated revenue, l_t is the log of employment, m_t is the log of deflated material and k_t is the log of capital. The error term is decomposed in two components $\varepsilon_t = \omega_t + \eta_t$. η_t is a standard measurement error or and ω_t is the technical efficiency shock, a state variable observed by the firm but unobserved to the econometrician. ω_t is assumed to be first-order Markov and is potentially endogenous as firms observe their shock before choosing their freely variable inputs l_t and m_t. k_t also responds to ω_t but with a lag as investments made in period $t-1$ come online in period t.

The innovation in the productivity shock $\xi_t = \omega_t - E[\omega_t|\omega_{t-1}]$ is unknown at the time the investment decision was made in $t-1$ and is therefore uncorrelated with current k_t. The control function approaches of Olley and Pakes (1996) and Levinsohn and Petrin (2003) both provide weak conditions under which there exists a proxy variable $h_t(k_t, \omega_t)$ that is a function of both state variables and that is monotonic in ω_t given k_t. The variables may include either investment (OP) or materials, fuels, electricity, or services (LP). Given the monotonicity there exists some function $g(\cdot)$,

$$\omega_t = g(k_t, h_t)$$

allowing ω_t to be written as a function of k_t and h_t.

Wooldridge (2009) uses a single index restriction to approximate unobserved productivity, writing

$$\omega_t = g(k_t, h_t) = \mathbf{c}(k_t, h_t)'\beta_\omega$$

where $\mathbf{c}(k_t, h_t)$ is a known vector function of (k_t, h_t) chosen by researchers with parameter vector β_ω to be estimated. The conditional expectation $E[\omega_t|\omega_{t-1}]$ can then be written as

$$E[\omega_t|\omega_{t-1}] = f(\mathbf{c}(k_{t-1}, h_{t-1})'\beta_\omega)$$

for some unknown function $f(\cdot)$, which Wooldridge (2009) approximates using a polynomial.

Replacing ω_t with its expectation and innovation, the estimating equation becomes

$$q_t = \beta_l l_t + \beta_k k_t + \beta_m m_t + E[\omega_t|\omega_{,t-1}] + \xi_t + \epsilon_t \tag{2}$$

$$[\xi_t + \epsilon_t](\theta) = q_t - \beta_l l_t - \beta_k k_t - \beta_m m_t - \mathbf{c}(h_{t-1}, k_{t-1})'\beta_\omega \tag{3}$$

We use materials m_t as the proxy but any other available proxy cited above could also be used here. Writing θ_0 as the true parameter value, Wooldridge shows that the conditional moment restriction

$$s(x_t;\theta) \equiv E[[\xi_t + \epsilon_t](\theta)|x_t] \text{ and } s(x_t;\theta_0) = 0$$

is sufficient for identification of β.