Determinants of Productivity

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Report

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1. Introduction

The ICT and Economic Growth project (commissioned by the Dutch Ministry of Economic Affairs, Innovation, and Agriculture, and carried out by Statistics Netherlands) aims to shed light on the determinants of economic growth in the Netherlands. The main research question is to investigate which components of economic growth are most important. Special attention is given to the role of Information and Communication Technology (ICT), in line with a substantial body of empirical evidence that ICT related factors are the main explanation of the gap between US and EU productivity performance. Moreover, we aim to investigate how different components are related. Again, there is special interest in the indirect effect of ICT on productivity via its impact on other factors, in line with its nature of General Purpose Technology (GPT). ICT does not only contribute directly to a firm's production as a part of the firm's capital stock, it also affects for example the innovative capacity of a firm and its flexibility to adjust to economic shocks. Moreover, there is increasing evidence on the need to complement ICT investment with for example organizational changes, and appropriate skills.

Past economic growth is key to the material well-being of people today. Economic growth, usually measured by growth in the gross domestic product, is therefore the focal point of economic policy, and accordingly, research about its determinants is vast and has a long history. Mathematically, growth in the volume of total production – which is how GDP growth can be interpreted – can be decomposed into two components, namely growth in labour, and the productivity of labour. In the face of ageing populations and increasing (international) competition, the latter component has gained crucial importance, and policy interest centers around it (e.g. Gelauff et al. 2004, and as exemplified by the Lisbon Agenda). Although the title of the project refers to economic growth, we will therefore in fact be focussing mostly on productivity, following also the lion's share of the literature on this topic. Labour productivity itself can be attributed to increases in capital intensity, as well as to the efficiency in which capital and labour are combined in the production process, referred to as total factor or, more modestly, multifactor productivity. Both sources will be discussed.

The current paper has three purposes. Firstly, we sketch a simple framework, that illustrates the measurement of productivity and highlights differences between two main approaches, namely production function estimation, and growth accounting. Given this framework it is also possible to point out where different subthemes fit into the total picture, and what is their mutual relation. Secondly, based on our reading of the literature, we discuss the main determinants of productivity growth, which are divided into three main categories. We also discuss main empirical findings from the literature. Given the sheer volume of research on this topic, it is necessary to be somewhat selective here, and we follow topics set out in leading existing overviews of related literature. Finally, we present a preliminary analysis of productivity growth in the Dutch business sector, based on industry data from the Dutch growth accounts. This empirical analysis extends the basic framework by considering heterogeneity in factors of production factors, and also introduces new variables that follow from our literature review.

2. Framework

To analyze economic growth it is useful to start from a production function based approach, where

$Y = f(K,L,E,M,S)$,

Y	gross output
K	capital input
L	labour
E	energy
M	materials
S	services

For ease of exposition we opt for a formulation in terms of value added, where value added is gross output minus intermediate inputs, i.e.

$VA = Y - (E + M + S)$,

and $VA = f(K,L)$.

Following the mainstream of literature we assume a Cobb-Douglas form for f, i.e.

$$VA = A \cdot K^{\alpha} L^{\beta} \Leftrightarrow A = VA/(K^{\alpha} L^{\beta})$$

where A is *MFP*. All variables are expressed in real terms (i.e. X_t and X_{t-1} are expressed in prices of a particular base year). In terms of growth we have

$$MFPG = A_t / A_{t-1} = \frac{VA_t /(K_t{}^{\alpha} L_t{}^{\beta})}{VA_{t-1} /(K_{t-1}{}^{\alpha} L_{t-1}{}^{\beta})} =$$

$$= \frac{VA_t / VA_{t-1}}{(K_t / K_{t-1})^{\alpha} (L_t / L_{t-1})^{\beta}} = \frac{QVA}{(QK)^{\alpha} (QL)^{\beta}},$$

where Q denotes a volume change. The elasticities of capital and labour (α and β) can be estimated by regression, or can be pinpointed at cost shares. Under neoclassical assumptions this would be equivalent.

We will contrast this approach with the index type approach used in the official Dutch growth accounts[1], which is a Laspeyres type index:

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[1] http://www.cbs.nl/nl-NL/menu/themas/macro-economie/publicaties/publicaties/archief/2012/default.htm.

$$MFPG = \frac{QVA}{\alpha QK + \beta QL} \ ,$$

with α and β equal to cost shares in t-1. Note that because $\alpha = K_{t-1}/(K_{t-1}+L_{t-1})$ and $\beta = L_{t-1}/(K_{t-1}+L_{t-1})$, we can write

$$\alpha QK + \beta QL = \frac{K_{t-1}}{K_{t-1}+L_{t-1}}\frac{K_t}{K_{t-1}} + \frac{L_{t-1}}{K_{t-1}+L_{t-1}}\frac{L_t}{L_{t-1}} =$$
$$= \frac{K_t + L_t}{K_{t-1}+L_{t-1}}$$

Therefore

$$MFPG = \frac{QVA}{\alpha QK + \beta QL} = \frac{VA_t / VA_{t-1}}{(K_t + L_t)/(K_{t-1}+L_{t-1})} =$$
$$= \frac{VA_t/(K_t + L_t)}{VA_{t-1}/(K_{t-1}+L_{t-1})} = \frac{MFP_t}{MFP_{t-1}} \ ,$$

where $VA_t/(K_t + L_t)$ is the implicit level of MFP in year t, analogous to $A_t = MFP_t = VA_t/K_t^{\alpha}L_t^{\beta}$ in the production function approach. While MFP and MFP growth are sometimes interpreted as the state and change in technology, the way it is derived shows that it may also capture measurement error and various phenomena that may or may not be accounted for in the model (like adjustment costs and economies of scale).

In general, the formula for MFP growth from the production function approach as well as from index theory, defines MFP growth as a ratio of the change in output divided by a function of the growth of capital and labour inputs:

$$MFPG = \frac{QVA}{g(QK, QL)} \ ,$$

where g can vary in functional form and different ways of weighting the changes in the inputs. MFP growth captures changes in the volume of output that can be produced by a given quantity of inputs, i.e. it is the shift in the production function (Hulten, 2001).

This simple methodological 'framework' will allow us to discuss how the different determinants fit into the analysis of productivity. It also makes clear a crucial distinction between growth accounting and econometric analysis. The first approach is based on decomposing overall productivity growth into the contributions of different components, where the magnitude of the contribution is crucially determined by the share of the component relative to other components. In contrast, econometric analysis is about the determination of correlations and causal effects of the determinants with productivity. If we view the firm's productivity level as a draw from a probability distribution (reflecting that there are many unobserved factors), these determinants can be thought to increase or decrease the probability of a positive draw for a firm (Syverson, 2011). Needless to say, both approaches have pros and cons, and it is the research question at hand that determines the most appropriate route.

An additional note is in place with respect to the analysis of complementarities. There is a growing body of evidence that, especially in the area of intangible capital, there are significant complementarities among factors of production. It is increasingly recognized that in order to increase performance, firms should invest simultaneous in multiple, complementary strategies. Especially Milgrom and Roberts (1990, 1995) are credited with this insight. The idea is that for a particular investment to yield, it is necessary for a firm to also make other adjustments. For example, if a firm invests in ICT, it benefits from the introduction of according changes in the organization that on the one hand help ICT to be more productive, and on the other hand need ICT to be effective. Such complementarities can be addressed and analysed quite straightforwardly in the framework proposed, through the introduction of cross-terms into the production function. For example, if two types of capital K_1 and K_2 are (expected to be) complementary:

$$\log VA = c + \sum_i \alpha_i \log K_i + \sum_i \beta_i \log L_i + \gamma \log K_1 \log K_2$$

It is worthwhile to note that specifying the production function in this way, the marginal effects of the complementary factors are a function of each other. In the example,

$$\partial \log VA / \partial \log K_1 = \alpha_1 + \gamma \log K_2$$

Thus, the direct effect of K_1 is increased or mediated by K_2. If α_1 and γ have opposite signs, it is possible to identify a non-linear effect, for example if $\alpha_1 > 0$ and $\gamma < 0$, the effect of K_1 is positive as long as $\log K_2 < \alpha_1/\gamma$.

The growth accounting approach does not allow for an easy incorporation of complementarities, but one can test if differences in productivity growth can be explained by them by first determining MFP growth, and subsequently relating this to the cross-term(s) of possible complementary factors. In the example:

$$MFPG = \gamma \log K_1 \log K_2 .$$

3. Overview of determinants found in literature

Based on our reading of the literature we will distinguish between three broad categories of determinants of economic/productivity growth:

1. input variables in the production process of a firm;
2. the business environment of a firm;
3. firm and industry dynamics underlying aggregate growth.

For each group we discuss the relevant determinants, the role of ICT, and the way to analyse the determinants within the model discussed above. Moreover, we point out where the analysis of the various determinants fits into the suggested methodological framework.

3.1. Input variables in the production process of a firm

The first group can essentially be characterized as variables over which the firm has control, i.e. they are the firms choice variables (sometimes called decision or control variables). Within this group we distinguish between capital and labour, as in the production function and index approach to measuring productivity. The main issue here is to distinguish between different types of capital and labour. In addition, one can distinguish a third input into the production process, which is knowledge. This can be partly embodied in tangible capital or in labour, but can also be the knowledge of an innovative way of producing, process, organizing or marketing a firm's product, which is difficult to attribute to one of the primary factors of production, and hence constitutes a factor of production in itself.

3.1.A. Capital inputs

3.1.A.1. Description

For capital, an important distinction is that between ICT-capital and non-ICT capital. ICT-capital can at its turn be subdivided in computers, software, databases, and telecom equipment, and various forms of ICT usage. Non-ICT capital is an aggregate of buildings, structures, and non-ICT equipment.

3.1.A.2. Role of ICT

Evidently, the role of ICT is clearly ICT itself as a form of capital. By distinguishing between ICT and non-ICT capital it is recognized that ICT may be a special part of capital that has different features from other types of tangible capital.

3.1.A.3. Heterogeneous capital in the model

The refinement of capital can be seen in the framework presented as the introduction of various types of capital instead of a homogeneous factor of production. That is, one introduces a vector of inputs $K = (K_1, K_2, ..., K_m)$. For each of these separate inputs one can estimate its contribution to productivity growth and/or its elasticity.

3.1.B. Labour inputs

For labour, it is possible to make distinctions in the quality of workers, for example concerning education, tenure, and age. It can be hypothesized that workers with higher skills contribute more to productivity, even after controlling for a higher compensation.

3.1.B.1. Role of ICT

There is evidence that the quality of labour and technology are complementary. Such complementarity also holds for ICT and skills. Thus, ICT may be used more effectively by a skilled worker compared to an unskilled worker, and vice versa, a skilled worker is more effective when she avails over ICT.

3.1.B.2. Heterogeneous labour in the model

The refinement of labour can be seen as the introduction of various types labour, that is one introduces vectors of inputs $L = (L_1, L_2, ..., L_m)$. For each of these separate types one can estimate its contribution to productivity growth and/or its elasticity. Alternatively, in the growth accounting framework, a possibility is to use a quality-adjusted price index for labour cost, thereby adjusting the labour input L, taking into the quality of labour in determining the contribution of labour to productivity growth.

3.1.C. Knowledge and innovation

It is also recognized in much of the literature that knowledge production can be seen as a productive asset for the firm. Knowledge creation includes human capital in the form of education and training, research, market development and organizational and managerial efficiency, see, Corrado, Haskel, Jona-Lasinio and Iommi (2012). The latter study recognizes this as the area where Europe and the US "arguably have their greatest comparative advantage". In fact, knowledge generation should be seen as a form of capital, in the sense that firms invest in the generation of knowledge, and build up a stock of knowledge that can thought to have similar features as tangible capital. A widely adopted model in this respect is that of Corrado, Hulten, and Sichel (2005), who capitalize intangible capital, distinguishing between knowledge in computerized information, about economic competencies, and firm-specific human capital in a growth accounting framework. Computerized information here includes software and databases, as discussed under ICT capital. The Dutch growth accounts includes these categories as part of the so-called Knowledge module.

Within the recent academic and policy debate there is also much attention for the phenomenon of so-called 'Big Data'. The OECD recognizes the "(…) explosive growth of "big data" and the economic value it generates" as a priority on the future research agenda. As is it goes with new phenomena, the notion of big data does not yet seem to be clearly defined, however. Broadly, it comprises investment in large databases, the ability to analyze these data, and to put this to use in the creation of business value. The empirical material is yet scarce, and statistical agencies do not gather information on this. Brynjolfsson et al. (2011) report that firms that use data-driven decision making (which entails the use of Enterprise Resource Planning, Supply Chain Management, and Customer Resource Management, in combination with the use Business Intelligence Systems), have about 5% higher productivity compared to other firms with similar ICT endowments.

In other studies using production functions, different variables related to the knowledge production of firms are often used to parameterize MFP (i.e. A) to explain differences in productivity (growth). Examples are R&D and innovation, where one can distinguish further between different types of innovation, e.g. technological and non-technological innovation. Measurement of innovation, however, is tricky, and studies usually rely on subjective firm-level surveys or patent information. Especially non-technological innovation, including different types of organizational and management practices, is hard to measure, although there is evidence that especially these types of investment makes or breaks successful enterprises (Bloom et al. 2012).

Finally, knowledge embedded in the firm's workers is of course an important factor, and is often captured in for example the share of workers with higher education. One can argue whether this is part of knowledge capital or whether it should be seen as a refinement of the firm's labour input. A useful distinction could be the difference between the (prior) education of workers, and the investment in training of a firm, which often has a firm-specific nature. In particular, it is possible to distinguish between different types of training, for example the investments in ICT-related training.

There is a range of policy issues around knowledge based capital, see OECD (2012). Such framework policies include tax environment, competition policy, education and training, intellectual property laws and enforcement, as well as policies that affect financing, and that deal with data security.

3.1.C.1. Role of ICT

The role of ICT in knowledge is partly that the intangible aspects of ICT are capitalized rather than expensed in the CHS framework. Moreover, as with skills, ICT is arguably complementary to many forms of knowledge. In particular, ICT and organizational change are found to be complementary in micro-studies (see e.g. Brynjolfsson and Saunders, 2010, for an overview). ICT helps in reorganizing a firm, while creating business value from ICT investment requires organizational change. Moreover, developments in ICT such as the online purchasing of products, has increased the value of knowledge based assets, in particular brand equity and reputation, which is about the image and trustworthiness of the selling party. Finally, ICT is seen as enabling technology that helps in the generation and sharing of knowledge. Thus, ICT enables innovation (see e.g. Spiezia, 2011), and helps in the diffusion of it.

3.1.C.2. Knowledge in the model

Specifying knowledge generation as inputs into the production function, can be done in various ways. Firstly, one can parameterize observed productivity differences or growth as a function of knowledge variables, as for example in the work by Griliches (1978) on R&D, and Crépon et al. (1998) on R&D and product innovation,

$$VA = A \cdot K^{\alpha} L^{\beta}$$

$$MFP = A = f(KNOW)$$

One can substitute A for $f(\cdot)$ and estimate the contribution of knowledge directly, or one can first estimate a standard production function, and relate knowledge to the residual in a second step. Complementarities may again be analyzed by adding cross-terms. A potential candidate for complementary variables is human capital. Moreover, different types of knowledge may be mutually complementary, for example combinations of innovation, types of ICT, and firm-specific human capital are worthwhile exploring.

The enabling effect of ICT may be captured further by adding an additional equation that determines knowledge as a function of ICT:

$$KNOW = f(ICT)$$

In a more growth accounting oriented framework, knowledge is capitalized and added to the capital services used by firms. Essentially it then becomes part of the vector of capital inputs $K = (K_1, K_2, \ldots., K_m)$. In this operation, output and the use of intermediate goods need to be adjusted, because one should take into account the knowledge production as a type of output, and in addition knowledge investments are typically included in categories of intermediate inputs (for example, cost of training is counted under services). Such a framework is sketched in the Corrado, Hulten, and Sichel papers, and implemented in for example the Knowledge module in the Dutch growth accounts.

3.2. The business environment of a firm

A firm operates in an environment that influences its behaviour. Syverson (2011) calls this the external drivers of productivity. Based on our reading of the literature and Syverson's overview the most prominent environmental factors seem to be the regulatory, policy and institutional environment, competition in product markets, and (knowledge) spillovers and externalities. Environmental factors determine to a large extent the responsiveness of market shares to exogenous shocks, and the process of entry and exit. By nature, they are the drivers of productivity that are most strongly linked to policy instruments, in the sense that they can be levers for policy makers to influence productivity growth. Again we discuss various determinants under these groups, the role of and relation to ICT, and finally ways to analyse these determinants in the framework.

3.2.A. Regulatory, policy, and institutional environment

A firm operates within a set of rules posed by national laws. For example, a firm's labour policy is subject to labour market regulation (LMR), the market in which it operates may be subject to (product market) regulation (PMR), and its production process may be subject to certain environmental regulations. These conditions determine to a large extent the actions of a firm.

Moreover, in order to be able to produce effectively, flexible access to inputs is also vital for firms. This flexibility is partly governed by the regulatory forces discussed above, but institutional features like the role of unions, the structure of the financial sector, as well as labour market conditions are crucial. For example, a shortage in the labour market of qualified labour is detrimental for growth. Also if access to finance is restricted, businesses are hampered in realizing their investment opportunities.

3.2.A.1. Relation to ICT

In general, strict regulations can be seen as hampering the flexibility of firms, and are therefore bad for productivity. ICT, on the other hand, makes firms more flexible. Thus, one can argue that firms that rely more on ICT, can easier cope with changes in the regulatory environment. Reversely, however, it can argued that under a strict labour market policy, firms adopt a careful hiring policy. This could hamper investing in ICT (or other forms of capital) if such investments require complementary hiring of employees with ICT skills (see e.g. Bartelsman et al. 2011).

3.2.A.2. Analysis of regulatory, policy, and institutional environment in the model

Assessing the effect of regulations requires variation in the regulatory environment for identification. Given that such regulations are often country specific, this usually requires cross-country data, or longer time-series that capture changes in regulation over time. For example, one can estimate the productivity within countries by applying a harmonized approach (as the framework above), and compare productivities for countries with different degrees of regulation. Or one can assess changes in productivity following a particular change in regulation within a country (for example, the deregulation of an industry, see e.g. Olley and Pakes, 1996). Also, one can compare the effects on productivity for other determinants conditional on the regulatory environment. For example, a study by the London School of Economics (Van Reenen et al. 2010) shows that the positive effect of ICT on productivity is tempered by the existence of strong LMRs and PMRs, both via a smaller positive effect on productivity at individual firm performance, as well as the fact that less productive firms are replaced at a slower pace.

3.2.B. Competition in the product market

Competition can arise from potential entry, price competition among incumbents on the national market, as well as from trade-induced pressures. It affects productivity in (at least) two ways. Firstly, it weeds out bad performing firms because the market will punish inefficiency (see e.g. Boone, 2000). The resulting dynamics is an important determinant of productivity, and will be discussed separately below under 3.3.B. Secondly, competition forces firms to become more productive in order to survive or gain market share. Too much competition, however, is not always good, as pointed out by e.g. Aghion et al. (2005). There may be a turning point in the effect of increasing competition, where firms under too much competitive pressure do not have the possibility to invest in productivity enhancing innovation anymore. It is a challenge for policy to find out a balance between competition, and for example the protection of property rights.

3.2.B.1. Role of ICT in competition

ICT has changed the nature of competition in recent years (Brynjolfsson en Saunders, 2010). ICT affects the way firms produce, how they gather information and communicate with customers, suppliers, and competitors. Firms that use ICT effectively can escape competition and achieve higher profitability, because of more efficient production, increased ability to collect information on market developments and flexibility to react to these market developments. Brynjolfsson et al. (2009) present evidence for a larger spread of productivity in ICT intensive sectors. On the other hand, in ICT intensive sectors as retail trade and business consultancy start-up costs are low, which increases competition. Thus, ICT and competition are important determinants of productivity, but the relation between them is complex.

Another aspect is competition in the digital economy. This has very specific features, which play at different market levels (Veugelers, 2012). Because network effects and economies of scale play a big role in markets for information products, it is for example difficult to draw a line between allowing for standardization and the prevention of anti-competitive behaviour. Moreover, because there is a need for products to be compatible, firms engage in collaboration, which is good for knowledge sharing, but also holds a risk of collusive behaviour.

3.2.B.2. Analysis of competition in the model

The effect of competition on productivity of incumbents can be analyzed by adding competition as an additional explanatory variable in the regression framework, as in Nickell (1996). There are a variety of candidates that may serve as indicators for competition, see Boone et al. (2007), and Polder et al. (2010), all of which may have their advantages and disadvantages in different contexts. One can also think of interacting the competition variable with other variables to see if the effects of other variables differ with the strength of competition. For example, Van Der Wiel et al. (2008) investigate the speed of convergence to the global and national frontier, depending on the degree of competition. Finally, given the endogenous nature of competition, researchers sometimes rely on changes in regulations (see 3.1.A) as instruments.

Competition is also by nature the force that drives the business dynamics that will be described in 3.3.B, and thereby also contributes to aggregate productivity via this route. To investigate the role of competition in this process, it is possible to analyse such dynamics under various regimes of competition, for example by comparing industries or countries, or within a particular aggregate before and after an identified change in competition policy.

3.2.C. Spillovers and externalities

A firm's productivity level can also be affected by other firm's production practices. Such spillovers and externalities are closely linked to the knowledge-based determinants under 3.1.C. The fact that knowledge is to a certain degree not appropriable, suggests there must be knowledge spillovers between firms. That is, firms may learn from other firms with respect to best-practice technology/ICT use and R&D. Moreover, there may be network effects from the use of technology, that is the value of using technology increases if other firms use it as well. Thus, spillovers are more related to knowledge (e.g. R&D), and network externalities are more related to the use of ICT (e.g. enterprise systems for intra-firm linkages).

This feature of 'knowledge-based capital' raises interesting policy issues, in that firms should have the incentive to invest in knowledge/ICT even if some of its value spills over to other firms. Finally, not all sorts of knowledge are subject to spillovers, for example brand equity and firm-specific human capital are highly excludable and non-rivalry (OECD, 2012).

3.2.C.1. Relation to ICT

There are various roles of ICT within this context. Firstly, ICT allows firms to gather information more easily and faster, so that it may be hypothesized that ICT using firms will benefit more from possible spillovers. Moreover, the use of ICT itself, like for example different types of e-business systems and e-commerce, may be subject to network effects, in the sense that the value of ICT increases if for example the firm's suppliers and customers also use ICT.

3.2.C.2. Analysis of spillovers in the model

A simple way to test for the presence of spillovers, is to add a measure for these spillovers in the production function, i.e. the productivity term A in the framework above is parameterized by a spillover variable. Naturally, the measurement of spillovers is a lot harder. Learning from best-practice is usually capture by a so-called distance-to-frontier (DTF), which measures the difference between a firm's productivity to the front-runner's productivity, see e.g. Bartelsman et al. (2006). It is possible to distinguish between different frontiers: for example the global and national frontier, or a firm may learn from firms inside and outside its market, or from firms and institutes (e.g. universities) close to its geographical location.

Spillovers from R&D can be captured by including aggregate R&D of other firms in the same market. Similarly, network effects from ICT are sometimes captured as the (aggregate) use/adoption of a particular type of ICT by other firms. While such analyses can produce results that are indicative for spillovers and positive externalities, the question of the nature of knowledge diffusion, and how learning by firms actually takes place, is not addressed.

3.3. Firm and industry dynamics underlying aggregate growth

Besides variables that impact the performance of firms directly, aggregate growth is also determined by the dynamics of its composing parts. Changes at the aggregate level can be decomposed into changes at the underlying levels.

3.3.A. Economic growth and industry growth

The gross domestic product (GDP) is the sum of the production (in value added) of all industries, and economic growth of a country (in terms of GDP growth) is determined by the economic growth of the underlying industries. Moreover, the size of an industry determines its weight in overall economic growth, and changes in the shares of industries are therefore also reflected in changes in aggregate growth. This phenomenon can be shown by a so-called shift-share analysis (see e.g. Van Ark, 2001) that splits the growth of the aggregate into a part relating to growth of the constituting parts, and a part related to changes in the relative size of these.

3.3.A.1. The role of ICT

The role of ICT in a study of industry dynamics can be twofold. Firstly, production may shift towards or away from to the ICT production industry. Secondly, ICT using industries may display a higher productivity growth than other industries, and, in addition or by consequence, may also be more successful in creating new jobs. Growth accounting studies by Van Ark, Jorgenson and others have shown that is an important explanation of the US-EU productivity gap.

3.3.A.2. Shift-share analysis in the model

In the notation of our model, let aggregate productivity be denoted by *P*, and the share of industry *j* as S_j. Then, a shift-share analysis could look like

$$\Delta P_t = \sum_j \Delta P_{jt} S_{jt} + \sum_j P_{j,t-1} \Delta S_{jt},$$

where the first part of the decomposition relates to changes in the industries' productivities ('intra-effect'), and the second part relates to changes in the relative size of industries ('shift effect'). Many refinements can be made to this decomposition, that enhance the interpretation. The purpose here is to show the basic principle, and how it fits the productivity framework. Finally, it is possible to distinguish different groups of industries, for example ICT producing, ICT intensive, and non-ICT intensive industries (see the contribution of Veldhuizen en Wittekoek). Note that $\Delta P_t = P_t - P_{t-1}$. For relative productivity changes P_t/P_{t-1} it is possible to take logs and proceed in the same way.

3.3.B. Industry growth and business dynamics

In a similar vein as above, industry dynamics itself can be decomposed into dynamics at the firm-level. In this case, firms grow or shrink just like industries do, but one must also take into account the contribution of attrition and new entry. A recurrent finding in the empirical literature is that these business dynamics, especially the process of reallocation where production factors are reallocated from less productive to more productive firms, are a major source of aggregate productivity growth (Bartelsman and Doms, 2001, Foster et al. 2002).

3.3.B.1. The role of ICT

Again ICT could increase the flexibility of firms, and therefore their ability to cope with economic shocks, which increases relative productivity and chances of survival. Thus, ICT can be an important determinant of the process of reallocation and exit. This is also related to the competition story above: competition moves market share toward more efficient producers, thereby increasing overall productivity.

In markets where the use of ICT is intensive, it is also found that there is a higher amount of turmoil: the productivity spread is higher and there is a higher turnover of firms in terms of entry and exit (OECD, 2012). Thus, ICT intensive are more risky, but in the end aggregate productivity will be higher as high-productivity firms survive and low-productivity firms get replaced by innovative and more productive new entrants.

3.3.B.2. Analysis of firm-level dynamics in the framework

In line with our previous notation, let P_j again denote industry productivity, and s_i the relative size of a firm *i* in industry *j*. Then a general decomposition into the contribution of continuing firms, and entry and exit, is

$$\Delta P_j = \sum_{i \in N} s_{it} P_{it} + \sum_{i \in C} s_{it} P_{it} - \sum_{i \in C} s_{i,t-1} P_{i,t-1} - \sum_{i \in X} s_{i,t-1} P_{i,t-1}$$

where *N*, *C*, and *X* are respectively the population of entrants, continuing and exiting firms in year *t*. Various ways have been proposed to further decompose the contribution of continuing firms *C*, which depends on an intra-firm and shift effect analogous to the industry case above, see Balk and Hoogenboom (2003). Specific examples of decompositions are Baily, Hulten, and Campbell (1992), Olley and Pakes (1996), and Petrin and Levinsohn (2003).

4. Main findings from the empirical literature

4.1.1. ICT capital

In the empirical macro-literature, a common finding is that the United States has seen a higher productivity growth over roughly the last two decades than most other countries, in particular when compared to the European Union (Van Ark et al. 2008). While institutional differences, like more flexible labour market regulations, and a higher degree of market competition may be part of the underlying factors explaining these differences, there seems to be a prevalent additional explanation to this phenomenon. International benchmarking exercises in growth accounting suggest that the rise of the knowledge economy is the most important explanatory factor in explaining the US-EU differences. In particular, as demonstrated by Jorgenson et al. (2008), the surge in productivity in the second half of the 1990s was driven by the high performance of the IT producing sectors, whereas after the beginning of the new century or so, aggregate productivity growth was determined mostly by the growth in heavy IT-using such as retail, trade and financial services. Jorgenson et al. conclude that the developments in the IT sectors and investments in IT enabled these sectors to create strongly innovative business processes. These insights by now have led to the consensus that the familiar Solow 'productivity paradox' has been solved. Industry data have also been used for regression based analysis. However, identification of an effect of ICT on MFP growth is difficult, especially when attempting to control for unobserved effects and endogeneity, suggesting the level of aggregation is not suitable for a causality analysis (Stiroh, 2004, Draca et al. 2006).

Although the growth accounting literature has presented convincing evidence on the role of IT in explaining productivity growth, there are several caveats. First of all, as noted by Brynjolfsson and Saunders (2010), these macro-economic trends do not explain why there is such a high degree of firm heterogeneity *within* countries. In particular, the advent of new forms of information and communication technology seems to have increased this heterogeneity in performance, even among firms which do not differ in their way of 'doing' IT. Secondly, growth accounting, by definition, is about decomposing high-level developments into components. Although it has proven to be a powerful and insightful tool, its results do not necessarily imply causality. To unravel the causal relations between productivity growth and its potential drivers, one may resort to econometric techniques, and in light of the heterogeneity mentioned above, many studies have shifted the focus to firm-level data.

In a much quoted study, Brynjolfsson and Hitt (2000) point out that the business value of IT is largely determined by how it is used. Especially complementary organizational changes (business processes, work practices) can be seen as a source of productivity growth. In turn, these changes also enable firms to develop new or improved products and services. Investment in IT complements changes in other aspects of the organization. For example, an important aspect of IT is that it reduces communication costs and facilitates monitoring. Internally, the use of IT can therefore lead to more efficient decision making, and a flatter, decentralized organization structure with higher worker responsibility. Moreover, with respect to a firm's external relations of the firm, IT reduces the benefits to vertical integration and creates the opportunity to rely on (specialized) outside suppliers. Finally, IT allows to reorganize the production structure to increase consumer benefits in terms of for example timeliness, customization, and offering new complementary services. Empirical evidence for existence of complementarities between workplace practices, organizational change and ICT is documented in a vast literature consisting of case studies as well firm-level econometric work. Examples include Ichinowski et al. (1997), Black and Lynch (2001), Crespi et al. (2007), and Bloom et al. (2012).

4.1.2. Human capital

Sianesi and Van Reenen (2003) present an extensive survey of the role of human capital in growth. They conclude there is substantial evidence for a positive effect of human capital on productivity. However, they find that, in contract to early endogenous growth models, the return to education diminishes over time. In addition, complementarities play an important role with human capital. Because of a higher skilled staff, a firm is able to invest in R&D and knowledge intensive capital. Caroli and Van Reenen (2001) find the organizational change has a higher impact on productivity in firms with more skilled workers. Moreover, they find that the complementarity between ICT and organizational innovation disappears when skills are taken into account. Bartel et al. (2007) find that firms increase their demand for skilled workers when investing in ICT, which is in line with the overall evidence on skill-biased technological change. Arvanitis (2005) present results for Switzerland, finding that human capital and ICT contribute positively to productivity, and also finds evidence for complementarity. However, there is no evidence for complementarity with organizational change. This study also provides a summary of various articles looking at the productivity effects of human capital, organizational change, and ICT, showing that results vary per setting. Finally, preliminary results in Hagsten and Sabadash (2012) present cross-country micro-level evidence from the ESSLimit project supporting the view that human capital complements ICT, especially education with a technical background (loosely referred to by them as IT-related human capital).

4.1.3. Knowledge

Based on the framework by Corrado, Hulten and Sichel (CHS), the contribution of knowledge based capital has been quantified in various countries. In the US, 27% of labour productivity can be attributed to investments in the knowledge capital categories distinguished in the CHS framework, while in Europe this amounts to 20 to 25% on average (with 22% in the Netherlands, see Corrado et al. 2012). A larger share is still due to MFP growth, namely about 30% in the US, and on average 42% in Europe (43% in the Netherlands).

Since studies highlighting the effects of organizational capital and its complementary nature to ICT and human capital have already been discussed above, we focus here mainly on micro-level studies of innovation here. The working horse model of the micro-economic literature on the productivity effects of innovation is the so-called CDM model, after Crépon, Duguet and Mairesse (1998). This model consists of three equations, where it is assumed that firms invest in R&D, which leads to innovation via a so-called knowledge production function (Griliches and Pakes, 1984). Ultimately, this knowledge feeds into the production function a separate production function. Accounting for selectivity issues arising from the fact that not every firm invests in R&D, and the endogeneity issues around R&D and innovation, Crépon et al. find a significant effect of product innovation on productivity. Many studies have performed analyses in the spirit of the CDM model, and have collaborated the results, see e.g. Klomp and Van Leeuwen (2006) for the Netherlands and Lööf and Heshmati (2006) for Sweden. Griffith et al. (2006) have extended the knowledge production function to include product and process innovation, but find that process innovation has a smaller impact on productivity.

In a study for the Netherlands, Polder et al. (2010) present evidence that both R&D and ICT lead to innovation. R&D is important for innovation in manufacturing, but not in services. The study distinguishes between product, process, and organizational innovation, and finds strong evidence that organizational innovation has the strongest productivity effects. Product and process innovation contribute to a higher productivity but only in combination with organizational innovation, which can be interpreted as evidence for complementarity.

Finally, it is worth mentioning the results by Spiezia (2011), who presents evidence from a cross-country micro-level project carried out at the OECD. The project finds evidence for the fact that ICT enables innovation. However, it does not find support that ICT also affects the degree of innovation in terms of innovation novelty. Somewhat surprisingly the study also concludes that ICT does not lead to an increase in the probability of collaboration on innovative activities, nor does it increase the probability of in-house development.

4.2.1. Regulation, policy and institutional factors

Rules, laws and institutional setting, determine the playing field in which a firm operates. Poor regulation or institutions can be detrimental to economic growth, while an appropriate institutional setting can help efficiency through solving market failures. For example, Bartelsman et al. (2011) finds that strong labour market regulations precludes investment in ICTs, which restricts the flexibility of the firm and markets, and in the end hurts economic growth. On the other hand, Olley and Pakes (1996) find evidence of aggregate productivity growth after deregulation in the US Telecom sector, which was mainly caused by a reallocation of capital towards more productive firms. Haskel and Sadun (2012) document a drop in average firm-level TFP in multi-store retail chains in the UK, following a change in regulation increasing the cost of opening large stores.

In a recent extensive study for the UK, Van Reenen et al. (2010), the most important policy conclusion is that high degrees of product and, especially, labour market regulation (PMR and LMR), temper the positive impact of ICT on productivity growth. Firstly, firms under tight LMR and PMR regimes are found to be restricted in the generation of business value from ICT. Secondly, the positive effect of ICT in fostering the process of reallocation of production factors towards more productive units, is hampered by the existence of strong LMR and PMR.

Government support for various kinds of firm's activities are usually aimed at increasing, in the end, to stimulate firm performance. For example, EIM/UNU-MERIT (2007), in their evaluation of the WBSO subsidy program for R&D, find that R&D subsidy stimulates R&D over and above the level that firms would have invested in absence of the program. They also find support for indirect increases in productivity in that firms with higher R&D have higher productivity. Since no effect on product innovation is found, they interpret this as a sign that R&D may lead to process innovation. In light of the discussion on spillovers below, however, one could also argue that R&D increases the absorptive capacity of firms, with respect to external knowledge.

4.2.2. Competition in the product market

Competition affects productivity through the allocation of market share and resources to more efficient firms, as well as through efficiency increases within firms (although there may be a trade-off within foregone innovation due to too much competitive pressure). In general it is found that competition fosters productivity growth, see e.g. Nickell (1996). Ahn (2002) provides an extensive overview of the literature, and evidence on interaction of competition with other variables such as innovation.

Two studies performed an analysis in the spirit of Nickell (1996) for the Netherlands. Felsö et al. (2001) used data for the manufacturing, construction, and trade sectors for the period 1985-1996. Productivity growth showed a significant positive correlation with the competition measures used: the profit elasticity, the

Herfindahl index, market share, and average firm size. Lever and Nieuwenhuijsen (1998) focussed on the Dutch manufacturing sector. They found that the increase of concentration in markets (in terms of higher market shares) leads to lower levels of productivity. Industries with relatively lower levels of market concentration, higher export shares and higher import shares show more than average growth of productivity. The authors further conclude that profitability has a positive and significant effect on productivity. According to the authors, this finding supports the Schumpeter hypothesis that monopoly profits are necessary for investments in research and development and innovation.

Finally, Polder et al. (2010) find that firms first experience a negative effect of increased competition, while in subsequent periods productivity is increased. A possible explanation is that firms need time to adjust, e.g. through investment in R&D or by making necessary adjustments in the production process, which may first have a disruptive effect but leads to productivity gains in later periods.

4.2.3. Spillovers and externalities

We distinguish three types of spillovers/externalities. Firstly, there are spillovers from best-practice production methods. A firm can learn from best-practices, as captured by its distance to some technological frontier. Bartelsman et al. (2006) find that the national technological frontier has a stronger impact on productivity growth of firms than does the global frontier. This means that firms learn more from their domestic counterparts. Moreover, the pull of the global frontier falls as the distance becomes larger. This means that if firms are too far from the global frontier they cannot catch up anymore. Consequently, if the national frontier is close to the global frontier, an economy may have the ability to catch up, but otherwise not. For policy purposes, the relevant question is whether to design policy to push the technological frontier, or stimulate efficiency and catching up. Van Der Wiel et al. (2008) corroborates the result that the national frontier is more important than the global frontier in the Netherlands. They also find important complementarities, in that competition provides an incentive for catching up to both frontiers, and that doing R&D facilitates the catching up process. The latter finding is in line with the 'two faces of R&D' argument by Griffith et al. (2004), who assert a basic level of R&D is required to be able to absorb the knowledge of other firms.

Secondly, there are spillovers from R&D, as analyzed by e.g. Griliches (1979, 1992). These are usually measured by aggregating R&D of other firms, possibly weighted according to technological or geographical distance. Cincera (2005) finds evidence for a positive effect of R&D spillovers on productivity for different ways of measuring such spillovers. Bloom et al. (2007) look at the balance between the positive effect of spillovers, and a possible market-stealing effect, and find that the former effect dominates.

Finally, there may be externalities from ICT usage. These can captured in the same way as R&D spillovers, as an aggregate of some measure of ICT, where each firm's/industry's contribution is weighted by an appropriate distance measure. Van Der Wiel and Van Leeuwen (2001, 2004) present firm-level evidence that such 'ICT spillovers' matter for the Netherlands. Mun and Nadiri (2002) also find that IT externalities can explain substantial parts of TFP growth in the US. However, Van Reenen et al. (2010) find no evidence of such productivity effects for the UK, although ICT adoption by neighbouring firms does have a positive effect on adoption. In a recent study under the ESSLimit project, Van Leeuwen and Polder (2012) also find evidence for cross-country spillovers for adoption of e-business systems within the firm's own industry. However, similar spillovers between firms in other industries within the same country are not apparent.

4.3.1. Industry dynamics

As mentioned above, the productivity gap between the US and EU is usually attributed to a smaller ICT industry in the latter, as well as a smaller growth of ICT-using sector. Using a shift-share analyses, Van Ark et al. (2003) find that the lagging behind of the ICT-using sector in the EU accounts for the largest part of the difference. This might be attributed to the presence of stronger regulations in Europe, especially on the labour market, and higher barriers to entry.

4.3.2. Business dynamics

One of the conclusion in the survey article by Pilat (2004) is that in an ICT-driven economy there is a lot of experimentation, where some firms succeed (and grow), and other firms do not (and exit). To seize the benefits of ICT, policy should create a business environment that cushions this process of creative destruction. This emphasizes the necessity of analysing micro and meso simultaneously, if one is interested in the sources of economic growth.

The question of the importance of such business dynamics to explain aggregate productivity changes has been attacked by various studies using decomposition techniques. Balk (2003) provides an overview of various decomposition techniques, including the ones by Baily, Hulten and Campbell (1992) and Olley and Pakes (1996). Balk and Hoogenboom (2003) find for the Netherlands that which decomposition one uses, matters for the conclusions about what is the most important component in aggregate growth. Foster et al. (2001) corroborate this conclusion in their review of the literature, but also find that the importance of entry is a robust finding in the empirical literature. Foster et al. (2002) finds that for the US services, the largest share of productivity growth is explained by new entrants replacing less productive exiting firms.

4.4. Concluding remarks on literature review

Our discussion of the literature is necessarily brief. There are topics that are not covered, like for example the influence of internationalization of markets and the increasing importance of global value chains. Each of the subthemes above could be the topic of a literature review in itself, in which case for each theme the review could easily tend more towards a book rather than a paper.

Our impression is that, although unified by a common cause that is the search for explaining productivity growth at different levels of aggregation, there is no unifying framework in which all these determinants can be gathered. Rather, what is found to be important in one branch of the literature, may be implicitly assumed away in another branch. However, we have identified the augmented production function as a common approach to assessing productivity effects, which can also be linked to the practice of growth accounting which is more rooted in index theory. We propose to start from this production function model, and analyze different determinants individually, highlighting possible cross-relations where possible.

5. Empirical results

The aim of this section is to provide an illustration and example of the production function framework, regarding the estimation of a production function on industry-level data. In addition to the basic production function specification, we distinguish between IT and non-IT (tangible) capital, add Corrado-Hulten-Sichel intangible categories, and add various cross-terms to test possible complementarities between IT and intangibles at the industry-level. Also we consider the extension of the framework by accounting for the quality of labour, and by adding determinants beyond factors of production like competition and spillovers.

All variables are sourced from the system of the Dutch Growth Accounts and the Knowledge Module. Production factors are measured as real costs (thus, for capital we have the real user costs, and for labour we have the real labour cost). We use data on 33 industries (within what Statistics Netherlands calls the 'commercial sector') for the period 1996 to 2008 (= 14 x 33 = 492 observations).

5.1 Standard Growth accounting and OLS estimation

Following Stiroh (2005) we depart from a specification based on gross output *Y*, using *j* for industry and *t* for years,

(1) $$\ln Y_{jt} = \ln A_{jt} + \sum_k \alpha_k \ln K_{kjt} + \beta L_{jt} + \gamma \ln M_{jt} + \delta_t D_t + \varepsilon_{jt}$$

where *K* is capital, *L* is labour, *D* is a year dummy, and ε a random disturbance. The A_{jt} variables represent an unobserved productivity shock. Aggregation over capital types may obscure considerable heterogeneity, which motivates us to distinguish different types of capital *K* (*k* = 1,…,5):

1. IT capital (only hardware), *KNIT*;
2. non-IT tangible capital, *KIT*;
3. Intellectual Property (*IP*) ;
4. Economic competencies (*EC*);
5. Computerized information (*CI*),

where the latter three categories are the Corrado-Hulten-Sichel (CHS) categories of capitalized knowledge (or intangibles). Moreover, we investigate various complementarities of IT capital with intangibles:

(1)' $$\ln Y_{jt} = \sum_k \alpha_k \ln K_{kjt} + \beta L_{jt} + \gamma \ln M_{jt} + \delta_t D_t + \phi_{13} \ln K_{1jt} \ln K_{3jt} + \phi_{14} \ln K_{1jt} \ln K_{4jt} + \phi_{15} \ln K_{1jt} \ln K_{4jt} + \varepsilon_{jt}.$$

According to neoclassical theory, the factor elasticities are equal to their cost shares. Table 1 gives the (average) cost shares for all factor considered. If estimated elasticities are above these costs shares, a factor can be said to earn above-normal returns. From table 1 it is clear that the IT part in both tangible and intangible capital is very small. Normal returns would therefore imply very low elasticities.

Table 1. Cost shares of production factors.

		unweighted	employment weighted
capital		0.164	0.144
	tangibles	*0.106*	*0.083*
	IT	0.004	0.005
	non-IT	0.102	0.078
	intangibles	*0.058*	*0.061*
	computerized information	0.007	0.007
	economic competencies	0.032	0.045
	intellectual properties	0.019	0.009
labour		0.311	0.414
intemediates		0.525	0.442

Turning to the estimations, because of possible heterogeneity due to differences in industry size, we use weighted OLS (based on log output), in line with Stiroh. We also employ fixed effects to account for industry-specific characteristics and measurement error.

Table 2 presents the results for various specifications. Each specification is estimated by OLS and fixed-effects (by including industry dummies, i.e. the 'within' estimator). The specifications are:

I. benchmark with (aggregate) capital, labour, intermediates;
II. like I with distinction between IT and non-IT capital;
III. like II, and CHS categories included;
IV. like III, but interaction terms of IT capital with CHS terms included.

For comparison we repeat the cost shares of each factor in the table.

In the basic specification we see that the OLS estimates differ somewhat from the cost shares, but are roughly in line. Capital and materials earn above normal returns, labour below. The picture shifts substantially using the fixed effects estimators, especially for capital which be-comes insignificant. This is in line with evidence reviewed by Stiroh and his own estimations for the US, although in our case aggregation over different types of capital may have a reinforcing effect. Under specification (II), we find that both IT and non-IT capital have strong positive (and 'above normal') productivity effects in the OLS estimation. However, non-IT capital drops to insignificance again when fixed effects are added, while also the labour elasticity drops dramatically. The return to IT capital, on the other hand, increases.

Specification (III) adds the CHS categories, and also shows contrasting results between OLS and FE. Under OLS, non-IT capital is significant, and IT capital is not, while under FE it is the other way around. Intellectual properties have a negative effect under OLS, while under FE it has a positive effect. For economic competences, we see the reversed picture: a positive effect under OLS, but negative under FE. The results for computerized information are consistent, but negative, which would mean a disappointing result about the contribution of IT.

Our most detailed specification also includes interaction terms between IT capital and the CHS categories. This specification gives in our view very interesting results. In the OLS esti-mation, both non-IT and IT capital earn significantly above normal returns. In addition, intellectual property has a strong and positive coefficient. By contrast, economic competencies and computerized information have negative direct effects. However, looking at the interaction terms puts the direct effects into a different light. Interestingly, the interaction terms all have the opposite signs of the direct effects of the CHS categories. Thus, the negative effect of economic competencies and computerized information turns into a positive effect when the value for (log) IT capital is high enough. Similarly, for intellectual property, the effect turns to negative when IT capital increases.

Table 2. Estimation results for various specifications.

	cost shares		I		II		III		IV	
	unweighted	weighted	OLS	FE	OLS	FE	OLS	FE	OLS	FE
capital	0.164	0.144	0.196***	0.031						
labour	0.311	0.414	0.233***	0.106***	0.215***	0.028**	0.163***	0.029**	0.211***	-0.035***
intemediates	0.525	0.442	0.590***	0.826***	0.591***	0.851***	0.564***	0.867***	0.572***	0.878***
non-IT	0.102	0.078			0.176***	-0.003	0.207***	0.003	0.196***	0.002
IT	0.004	0.005			0.030***	0.057***	0.008	0.062***	0.052***	-0.029
intellectual properties	0.019	0.009					-0.038***	0.091***	0.223***	-0.027***
economic competencies	0.032	0.045					0.091***	-0.031***	-0.055***	0.142***
computerized information	0.007	0.007					-0.026***	-0.021***	-0.147***	-0.068***
interaction of IT with										
intellectual properties									-0.072***	0.043**
economic competencies									0.027***	-0.041***
computerized information									0.032***	0.019***

Significance levels: * = 10%, ** = 5%, *** = 1%. Dependent variable is log gross output. All variables are in logs. Weighted cost shares are weighted by employment. OLS and FE use output weights. We also include year dummies to capture technological progress and time specific measurement error.

Thus, we find a non-linear effect for the CHS categories, depending on the magnitude of IT capital in an industry. Note that the marginal effects for the CHS categories (K_k, k = 3,4,5) depends on IT capital (K_1)

$$\partial \log Y / \partial \log K_k = \alpha_k + \phi_k \log K_1.$$

So that, if α_k and ϕ_k have opposite signs, the sign of the marginal effect flips if

$$\log K_1 > -\alpha_k / \phi_k.$$

Given the results, this implies the points of infliction in table 3. The share of observations gives the number for which IT capital is above the threshold. Thus, we find that while intellectual property has a positive direct effect on productivity, the effect changes to negative when $\log K_1$ = 3.084, which is true for almost 80% of the observations. In most cases, the effect of intellectual property is negative, therefore, and there seems to be substitution rather than complementarity with IT capital. On the other hand, economic competencies has a negative direct effect, but the effect changes to positive with IT capital, and in about 96% of observations its effect will be positive, pointing at strong complementarity between this type of intangibles with IT capital. Computerized information has a positive effect in about 20% of the cases. There is again a lot of contrast of the OLS with the FE results, where the effect of intellectual properties is de facto positive, economic competencies has a negative effect in 67% of the cases, and computerized information has a positive effect in 63% of the cases.

Table 3. Infliction points for the marginal effect of CHS categories

(value for $\log K_{jt}$ where sign of effect changes).

	OLS	% obs	FE	% obs
intellectual properties	3.084	0.797	0.623	1
economic competencies	1.990	0.958	3.461	0.674
computerized information	4.612	0.203	3.550	0.634

In summary, we find the following. There are large contrasts between OLS and FE results. However, in almost each specification IT capital earns an above normal return. Moreover, the effect of intangibles is found to interact with IT capital. At face value, the OLS estimations seem more plausible, especially in relation to the cost shares of the various inputs. In particular the elasticity of labour seems implausibly low in the FE estimations, even turning to negative in our most elaborate specification. However, our estimations may suffer from omitted variable or simultaneity biases. The section 5.3 we look at two recently suggested alternative estimation approaches that are often used for production function estimation in the literature. Firstly, however, we extend the model with additional variables that may impact productivity.

5.2 Extending the model with new variables

5.2.1 Adjusting labour input for quality

Consider the average labour cost per hour in year t, $\frac{LC_t}{h_t}$ and its equivalent in t+1, $\frac{LC_{t+1}}{h_{t+1}}$. The value index of labour cost is $\frac{LC_{t+1}}{LC_t}$, and the volume index of labour based on hours worked is $\frac{h_{t+1}}{h_t}$. Using that the volume index is the value index divided by the price index, we have

$$pi_t^L = \frac{\frac{LC_{t+1}}{LC_t}}{\frac{h_{t+1}}{h_t}} = \frac{\frac{LC_{t+1}}{h_{t+1}}}{\frac{LC_t}{h_t}}$$

This is the common (implied) price index of labour. It is clear that this index does not account for the fact that the quality of an hour worked is different for different types of labour. For example, the price index drops if relatively young workers – with lower wages – enter the market. However, this drop is then caused by a compositional effect rather than a change in the price of labour.

Recently, CBS has developed a price index for labour cost that corrects for changes in the composition of labour (see Van Den Berg and Peltzer, 2011). Analogous to the consumption price index, labour is divided into various categories related to the "quality of labour". For each cell, one can calculate the average labour cost per hour. To avoid that compositional effects play a role in the aggregate price index, one can determine the distribution of hours worked over the various cells in a particular base year. By weighting the average labour cost by the distribution in the base year, one obtains a price index that is free of composition effects. Essentially, one weighs together the per hour labour cost in each category, imposing that the distribution of hours worked over the category does not change.

By using the pure price index of labour, call it $pi_t^L(QA)$, where QA denotes "quality adjusted", we achieve that the quality of labour is included in the volume of labour (i.e. deflated labour cost). The difference between the two indices, $pi_t^L - pi_t^L(QA)$, is labelled the "compositional effect" ("structuureffect" is the Dutch term that Van Den Berg and Peltzer maintain).

5.2.2 Capturing spillovers

To operationalize spillovers between industries, we consider first a way of measuring the strength of linkages between them. A natural way of doing so is to consider input-output (IO) tables, in which the total supply and use by industries are split into their source and destination industries. Let the supply of industry *i* to industry *j* be denoted by s_{ij}, and likewise the use of industry *i* coming from industry *j* by u_{ij}. Total supply and use of industry *i* are denoted s_i and u_i respectively, so that the share of industry *j* in total supply and use of industry *i* is

$$w_{ij}^{sup} = s_{ij}/s_i,$$
$$w_{ij}^{use} = u_{ij}/u_i.$$

How much a certain industry can learn from another, depends how strong the linkages between the industries are. The rationale for this is that firms have contact with suppliers and users, and learning goes through those contacts. There are various things that firms can learn about, such as knowledge generating from R&D, adoption of new technologies, and best-practice organization of business processes in other industries. Besides these knowledge spillovers, an industry is also affected simply by how well its main supply chain partners are doing: if demand for bread decreases and bakeries have hard times wheat farmers will be affected as well.

As a catch-all proxy to the performance of a particular industry we consider its (multifactor) productivity growth (*MFPG*). This embodies both knowledge generation as well as changes in demand conditions.[2] We construct two spillover measures by weighing MFPG by shares in supply and use:

$$SPILL\_SUP_{it} = \sum_{j\neq i} w_{jt}^{sup} MFPG_{jt}$$

$$SPILL\_USE_{it} = \sum_{j\neq i} w_{jt}^{use} MFPG_{jt}$$

There are various alternatives to these measures, which we leave for further exploration at the moment. These include 1. The use of alternative knowledge variables (e.g. investment in R&D and/or ICT, and productivity levels rather than growth); and 2. Restricting *MFPG* to being a. positive or b. larger than *MFPG* in the industry *i* itself (while we now capture how an industry is affected by all other industries, it can be interesting to limit *MFPG* to those industries achieving growth, or even higher growth than the pertinent industry, i.e. the industries it can actually learn from).

[2] Productivity is mainly affected through the fact that production factors as capital and labour are fixed or quasi-fixed in the short-run. Under declining demand for its products, firms can usually not easily shed workers or capital, which means that while output is cut back, factor costs are staying up.

5.2.3 Measuring competition

While there have been suggested many ways to assess competition, there is no definitive measure for this concept yet (Boone et al. 2007, Polder et al. 2010). For the moment, we opt for a metric that is simple compute at the industry level, namely the Price Cost Margin

$$PCM = (Y - E - M - S - L)/Y.$$

Alternatively, it is possible to calculate mark-ups at firm-level (see the contribution by Van Leeuwen in this project), and take the average or median of those to arrive at an industry-level indicator. Another alternative is to use the profit elasticity (or 'Boone' indicator, after Boone, 2001), which can be estimated from firm-level regression by industry. We leave the implementation of the alternative competition indicators for future research.

5.2.4 Estimation results with additional variables

Controlling for quality of labour
Table 4 presents the OLS estimation results for the industry productivity regressions. Since the price index used to derive a quality corrected volume index for labour is available only for the period 2002-2008, we also re-estimate the regression without controlling for quality, to avoid that the comparison is affected by the time period used (recall that the estimations in Table 2 above were carried out for the period 1996-2008).

Looking first at the differences caused by estimation on the basis of the shorter time period, we see that most are non-substantial. However, it seems that the effect of IT capital is estimated to be stronger in the latter period, which is consistent with an increasing of importance of IT capital over time.

When considering the differences between the estimations based on labour volumes derived from changes in hours worked and those derived from a quality adjusted volume index, differences are also negligible. While we see that the estimated labour elasticity increases slightly, the differences are non-significant. Other coefficients are also barely affected. However, we see that IT capital becomes insignificant when controlling for quality of labour. This is an interesting finding, since it suggests that industries with higher IT capital may also have higher quality labour, and failing to control for the latter attributes higher productivity to IT capital.

Although controlling for labour seems relevant in our context of investigating the relation of productivity and IT, we will opt for the original labour volumes based on hours worked in the remaining estimations in the paper, because of the limited period for which quality adjusted figures can be constructed. For future research, we aim to investigate the possibility of making a longer time-series of quality adjusted labour volumes.

Adding spillovers

Table 5 shows the results for our two base specifications when adding measures of spillovers. As discussed above we distinguish between spillovers from supplying industries and spillovers from using industries. Surprisingly, we find strong negative effects associated with our spillover indicators. This holds for both spillovers from suppliers and users, and in both the specifications with and without interactions. In the latter specification, we do not find evidence of any interaction of spillovers with IT capital. Finally, we have also investigated whether there may be a lag for knowledge to transfer from one industry to another, by including lagged spillovers. The results of these estimations are not reported, but are similar to those reported in Table 5.

Clearly, the negative effect on our spillover measures runs against the intuition of industries benefiting from knowledge generation in upstream or downstream industries. Thinking about what could be driving these results, our tentative interpretation is that industries that perform well (in terms of MFP growth) may have increased market power. This could affect their ability to set or negotiate prices. That is, suppliers set higher prices if demand for their product increases, and users with market power negotiate lower prices (e.g. retailers putting pressure on suppliers to reduce prices). Thus, our indicator may in fact be picking up market power of up- and downstream industries, which is negatively related to performance.

Further research should investigate of other variables than MFP growth in the spillover measure. This could include labour productivity and investment in R&D and/or ICT.

Adding competition

Table 6 shows the results for adding the competition variable (nb. we use log(1-PCM), as PCM itself is inversely related to competition). In the specifications in the left panel, competition is added as an explanatory variable and interacted with IT capital. We find a strong negative effect, especially in the specification without interactions. Moreover, we find that the coefficients of capital and labour are substantially affected. Non-IT capital obtains an implausible negative effect, while the labour coefficient almost doubles with respect to earlier OLS estimations. In our view, this is caused by the fact that PCM is a function of output, labour and intermediate inputs, leading to collinearity with the other variables.

Therefore, instead of using the PCM variable as an explanatory variable, we use it to perform a sample split of high and low competition regimes, based on the median value of PCM. The results for this sample split are in the right panel for the specification without interactions only. We find that in the low competition regime, non-IT capital is more important than IT-capital, and the latter is even associated with a negative effect on performance. Moreover, economic competencies and computerized information positively affect performance. Conversely, IT capital is more important in the high competition regime, where non-IT capital is not significant. Whereas the elasticity of economic competencies and computerized information are now insignificant, intellectual properties now have significantly negative effect. A loose interpretation of the differences between the low and high competition regime could be that under low competition firms have the chance to invest in and reap the benefits of innovation (intangibles), whereas under high competition firms are forced to work more efficiently by automizing through IT.

We have also experimented with a squared competition term to investigate a possible non-linear effect. Aghion et al. (2005) and various other empirical studies have identified an inverted U-shape relation between innovation and competition. Such a relation may carry over to productivity if productivity is a linear function of innovation. However, in unreported estimations, we do not find evidence for such a relation. (Rather, we find a positive sign on the quadratic term.)

Further research should focus on the use of more sophisticated measures of competition, as the profit elasticity and mark-ups, both of which are derived from firm-level regressions.

5.3 Econometric considerations

To account for endogeneity of inputs one finds various methods in the literature, see e.g. Griliches and Mairesse (1998) and Arellano and Honoré (2001). One can distinguish two types of main approaches. Firstly, there is the 'Dynamic Panel Data (DPD)' approach, in the spirit of Arellano and Bond (1991), and developed further by among others Arellano and Bover (1995) and Blundell and Bond (1998, 2000). Secondly, there is the 'structural' approach as advocated by Olley and Pakes (1996) and Levinsohn and Petrin (2003), more recently extended by Ackerberg, Caves and Frazier (2006).

We discuss and apply both the approaches by Blundell and Bond (BB) and Ackerberg, Caves and Frazier (ACF). From our reading of the literature, these two approaches represent the 'state-of-the-art' in both lines of literature. Recent applications of both types of estimators can be found in Dobbelaere and Mairesse (DPD, 2013), and De Loecker et al. (ACF, 2013).

5.3.1 Blundell-Bond estimator

Blundell and Bond (1998a, 1998b) suggest a GMM-type estimator to solve the problem of endogeneity, see also Van Der Wiel and Van Leeuwen (2003). The estimator is also known as the SYS-GMM estimator, due to the fact that a system of equations in estimated (namely the estimation equation in levels and in first-differences). Comparing different estimation strategies, Stiroh (2005) prefers this approach.

Ignoring any additional production factors besides capital (K_{it}) and labour (L_{it}) for notational simplicity, the estimating equation can be written as (small case means logs)

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \alpha_i + \omega_{it} + \epsilon_{it}$$

$$= \beta_k k_{it} + \beta_l l_{it} + \alpha_i + \psi_{it}.$$

If ω_{it} follows an AR(1) process, i.e. $\omega_{it} = \rho\omega_{it-1} + e_{it}$, the equation can be written as a dynamic reduced form equation

$$(*)\ y_{it} = \pi_1 k_{it} + \pi_2 k_{it-1} + \pi_1 k_{it} + \pi_3 l_{it} + \pi_4 l_{it-1} + \beta_l l_{it} + \pi_5 y_{it-1} + \alpha_i^* + w_{it},$$

where w_{it} denotes a composite error term.

Differencing removes the fixed effect (α_i), and under standard assumptions, this yields the moment conditions,

$$E[x_{it-s}\Delta w_{it}] = 0$$

where $x = \{k, l, y\}$, and for $s \geq 2$ or $s \geq 3$ depending on the presence of measurement error. Estimation with GMM using these moment restrictions was first suggested by Arellano and Bond (1991).

However, first-difference GMM estimators such as that of Arellano and Bond (1991) have been found to have large finite sample bias and poor precision when the lagged levels are weak instruments for the differenced variables. Blundell and Bond (1998) suggest to extend the set of moment restrictions with lagged differences. If the differences in x are unrelated to the fixed effect,

$$E[\Delta x_{it-s}(\alpha_i^* + w_{it})] = 0$$

for s = 1 or 2, depending on measurement error (and moments for larger s can be shown to be redundant). Note that the second set of the moment restrictions does not require the actual estimation of α_i^*, since it is the composite term $(\alpha_i^* + w_{it})$, and this can be calculated directly from (*) for given candidate parameter estimates.

The complete set of moment restictions is used to obtain a GMM estimation of the reduced form parameters. Finally, the structural parameters β can be derived from a Minimum Distance procedure, noting that $\pi_5 = \rho$, $\pi_1 = \beta_k, \pi_2 = -\rho\beta_k, \pi_3 = \beta_l$, and $\pi_4 = -\rho\beta_l$ (see e.g. Wooldridge, 2003).

5.3.2 Olley and Pakes

In a seminal paper, Olley and Pakes (1996) considered the estimation of the model

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \epsilon_{it}$$

Unlike the DPD literature, their approach does not consider a fixed effect. Similar to the DPD literature, however, a first-order Markov process is assumed for ω_{it}. The main insight of Olley-Pakes is that if one can assume that investment is a non-monotonic function of productivity ω_{it} (and other state variables like capital), one can invert this function to obtain ω_{it} as a function of investment. This gives

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f_t^{-1}(i_{it} k_{it}) + \epsilon_{it} =$$

$$= \beta_l l_{it} + \Phi(i_{it} k_{it}) + \epsilon_{it}$$

In the first stage of the estimation $\Phi(i_{it} k_{it})$ is approximated non-parametrically by a polynomial in i_{it} and k_{it}. Thus, one obtains an estimate of β_l and $\Phi(i_{it} k_{it})$. To obtain an estimate of β_k, it is noted that

$$\omega_{it} = E[\omega_{it} | \omega_{it-1}] + \xi_{it}$$

where ξ_{it} is orthogonal to all information available at time t-1. Since Olley and Pakes assume that the level of k_{it} is determined at t-1, it holds that

$$E[\xi_{it} k_{it}] = 0.$$

Noting that $\omega_{it}(\beta_k) = \widehat{\Phi}(i_{it} k_{it}) - \beta_k k_{it}$, we can construct ξ_{it} as a function of β_k

$$\xi_{it}(\beta_k) = \omega_{it}(\beta_k) - \hat{E}[\omega_{it}|\omega_{it-1}]$$

where $\hat{E}[\omega_{it}|\omega_{it-1}]$ can be obtained from regressing $\omega_{it}(\beta_k)$ on $\omega_{it-1}(\beta_k)$. Thus, the moment restriction

$$E[\xi_{it}(\beta_k)k_{it}] = 0$$

can be used to obtain an estimate of β_k.

5.3.3 Ackerberg-Caves-Frazier

Although an innovative breakthrough in the estimation of productivity, the Olley-Pakes methodology has a couple of drawbacks that have been noted in the literature (Griliches and Mairesse, 1995, Levinsohn and Petrin, 2003, Ackerberg et al 2006, Wooldridge, 2009). Firstly, investment in physical capital incurs substantial adjustment costs. If there are non-convex components in these adjustment costs (i.e. a fixed component), there will be substantial zero-investment at the firm-level. The latter is unfortunate in the OP approach, because (for technical reasons) it requires non-zero investment, and observations where this does not hold are discarded. Levinsohn and Petrin suggest to use intermediate inputs as a proxy for the unobserved productivity instead, although, for identification, this requires the strong assumption that labour and intermediate inputs are determined independently as pointed out by Ackerberg et al. Secondly, the unobserved productivity is assumed to be a function of a single state variable, which is log investment in the original Olley-Pakes article. This is restrictive, especially in our context of heterogeneous capital, and the inclusion of various forms of intangible capital.

Ackerberg et al. also show that the Levinsohn-Petrin approach suffers from a collinearity problem, in the sense that the term controlling for the unobserved productivity of a firm in the first stage estimation, is a function of employment, of which it is the goal to identify the parameter in the first stage. They show that the method can be “saved” by particular assumptions on the timing of decision making about inputs, and the correlation structure, but these are all very restrictive.

The alternative procedure by Ackerberg et al. closely resembles that of Olley and Pakes. However, as suggested by Levinsohn and Petrin they use intermediate inputs instead of investment to construct the inverse productivity function f_t^{-1}. Moreover, they assume that labour is determined before intermediate inputs, which makes labour a state variable at the time that intermediate inputs are decided, and hence labour enters into f_t^{-1}. Finally, given the collinearity problems of the Levinsohn-Petrin approach, Ackerberg et al. refrain from identifying any coefficients at the first stage. Thus, they estimate

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} =$$

$$= \Phi(k_{it}, l_{it}, m_{it}) + \epsilon_{it}$$

Now we have that $\omega_{it}(\beta_k) = \widehat{\Phi}(k_{it}, l_{it}, m_{it}) - \beta_k k_{it} - \beta_k l_{it}$. Analogous to Olley and Pakes we can use the moment restriction

$$E[\xi_{it}(\beta_k) k_{it}] = 0$$

where

$$\xi_{it}(\beta_k) = \omega_{it}(\beta_k) - \hat{E}[\omega_{it}|\omega_{it-1}]$$

and $\hat{E}[\omega_{it}|\omega_{it-1}]$ can again be obtained from regressing $\omega_{it}(\beta_k)$ on $\omega_{it-1}(\beta_k)$.

To identify β_l we need an additional moment restriction. Since l_t is not determined at time t-1, it is not orthogonal to ξ_{it}, but its lag can be used:

$$E[\xi_{it}(\beta_k) l_{it-1}] = 0.$$

5.4 Results and comparison of methods

One faces various choices in modelling the production function, all of which can possibly affect outcomes. To illustrate differences between the Blundell-Bond and the Ackerberg-Caves-Frazier methodologies, we employ our two basic specification with the CHS categories and interactions with IT capital:

$$y_{it} = \beta_{knit} knit_{it} + \beta_{kit} kit_{it} + \beta_l l_{it} + \beta_l IP_{it} + \beta_l EC_{it} + \beta_l CI_{it} + \epsilon_{it}$$

$$y_{it} = \beta_{knit} knit_{it} + \beta_{kit} kit_{it} + \beta_l IP_{it} + \beta_l EC_{it} + \beta_l CI_{it} +$$

$$+\beta_{kip} kit_{it} IP_{it} + \beta_{kec} kit_{it} EC_{it} + \beta_{kci} kit_{it} CI_{it} + \epsilon_{it}$$

5.4.1 Blundell-Bond estimations

In Table 7, we report the results for the Blundell-Bond estimator. We use a gross-output specification (preferred by Stiroh, 2005, and Basu and Fernald, 1997), and a value-added specification (preferred by Bond and Söderbom, 2005). The latter specification makes it easier to compare with the results of the ACF method. To compare with ACF, we have also assumed that capital is predetermined so that t-1 values can be used as instruments. Other variables (labour and the CHS categories) are endogenous (t-2 values are used as instruments). The estimations are done with the Stata command xtdpdsys, followed by a minimum distance procedure to back out the structural parameters (see above).

The results show some striking differences, both between the value added and gross output specification, as well as between the specification with and without interactions. Starting with the GO specification without interactions, we find approximate constant returns to scale, with IT capital earning strong above normal returns. The labour coefficient is on the low side. Of the CHS categories, intellectual property contributes positively, whereas economic competencies are associated with a negative contribution. Turning to the specification with interaction terms, IT capital still earns substantial above normal returns, while the labour coefficient is closer to the cost share in this case. The pattern found for the CHS productivity effects is quite different now, with economic competencies having a significant positive direct effect. However, this is compensated by a negative interaction effect with IT capital. Thus, as IT capital increases, the effect of economic competencies turns from positive to negative. On the other hand, interaction effects of IT capital with intellectual property and computerized information are positive, while there is no direct effect. Thus, under this specification, intellectual property and computerized information increase productivity only conditional IT capital.

Turning to the value added specification, the magnitude of the labour coefficient increases stronger than capital when comparing with the gross output specification. The elasticity of IT capital even drops with respect to the gross output specification, which is unexpected. Of the CHS categories, only computerized information is positive and significant, which also contrasts with the GO specification. Looking at the VA specification with interactions, the significance of capital is wiped out. However, intellectual property and economic competencies are now positive and significant. The interaction of economic competencies and computerized information with IT capital are positive and significant as well. Again, this pattern contrasts somewhat with the findings in the gross output case.

5.4.2 Ackerberg-Caves-Frazier estimations

Table 8 shows the results for the ACF method. In entering the 'additional' CHS variables, we prefer to enter them in the parameterization of the productivity state ω_{it}, see also De Loecker et al. (2013). In principle, since these variables can be regarded as factors of production analogous to capital and labour, it would make sense to treat them in the same way and enter them directly in the production function. However, in the ACF method we run into a practical problem as strictly speaking these variables – as well as their interactions and squares – need to be included in the polynomial used in the first stage estimation. With an eye on the limited number of observations in our industry panel, this would lead to too many variables. By including the (lagged) CHS categories in the autoregression for productivity, we are essentially assuming that the current (unobserved) productivity is determined by past productivity and intangible assets.

The left panel shows the results for a specification without interaction terms. This reveals another practical problem with this specification. In regressing $\omega_{it}(\beta_k)$ on $\omega_{it-1}(\beta_k)$, we find that the coefficient on $\omega_{it-1}(\beta_k)$ is statistically equal to 1. In our understanding, this means that there is a lot of persistence in industry level productivity. The consequence is that the estimation of ξ_{it} that follows from this estimation is very close to zero. In turn, this makes identification of β_k and β_l very difficult, of which the results in the left panel of Table 8 offer a clear testimony. Clearly, the estimates of capital and labour are not 'ball-park' figures.

An alternative is to let go off the assumption that ω_{it} follows a first-order Markov process (see also De Loecker et al. 2013). Then the unobserved productivity state is determined by (lagged) intangibles only. The estimation procedure itself remains essentially the same. The results for this specification with and without interactions are presented in the right panel of Table 8. They show a relatively high elasticity of non-IT capital. The elasticity of IT capital is also above its cost share in the specification without interactions, and increases significantly when interactions are added. The labour elasticity is estimated below its cost share in both specifications. Finally, the effect of intellectual property is negative, and that of economic competencies is positive in the specification without interactions. When adding interactions, the direct effect of intellectual property turns to positive, while the interaction with IT is negative, meaning that as IT increases the effect of intellectual decreases and eventually turns negative. The direct effect of economic competencies turn insignificant, but its interaction with IT is positive. Computerized information has a negative direct effect, but as IT increases this effect increases and turns positive, as the interaction is found to be significantly positive.

5.5 Summary and discussion of results

~ to be completed ~

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Table 4. OLS estimation results with quality adjusted labour.

	Non-adjusted labour						Adjusted labour					
N = 229	coeff		se	coeff		se	coeff		se	coeff		se
non-IT	0.208	***	0.017	0.200	***	0.016	0.225	***	0.017	0.217	***	0.016
IT	0.048	*	0.027	0.113	*	0.069	0.029		0.026	0.092		0.067
labour	0.138	***	0.025	0.196	***	0.026	0.140	***	0.024	0.197	***	0.025
intermediate inputs	0.605	***	0.026	0.604	***	0.027	0.602	***	0.025	0.599	***	0.027
intellectual properties	-0.035	**	0.014	0.203	***	0.052	-0.036	***	0.013	0.196	***	0.051
economic competencies	0.062	**	0.032	-0.015		0.072	0.069	**	0.031	0.002		0.070
computerized information	-0.030		0.019	-0.195	***	0.059	-0.032	*	0.019	-0.199	***	0.057
interaction of IT with												
intellectual properties				-0.066	***	0.014				-0.065	***	0.014
economic competencies				0.009		0.014				0.007		0.014
computerized information				0.044	***	0.015				0.045	***	0.015

Table 5. OLS estimation results with spillovers.

N = 429	coeff		se	coeff		se
non-IT	0.209	***	0.004	0.198	***	0.004
IT	0.011		0.007	0.036	*	0.021
labour	0.159	***	0.006	0.209	***	0.007
intermediate inputs	0.574	***	0.006	0.583	***	0.006
intellectual properties	-0.037	***	0.004	0.219	***	0.015
economic competencies	0.094	***	0.008	-0.060	***	0.017
computerized information	-0.023	***	0.005	-0.141	***	0.014
spillovers from suppliers	-2.248	***	0.360	-3.231	**	1.474
spillovers from users	-1.407	***	0.186	-1.325	**	0.667
interaction of IT with						
intellectual properties				-0.071	***	0.004
economic competencies				0.030	***	0.004
computerized information				0.031	***	0.004
spillovers from suppliers				0.052		0.319
spillovers from users				0.040		0.158

Table 6. OLS estimation results with competition.

N = 429	coeff		se	coeff		se	coeff		se	coeff		se
non-IT	-0.034	***	0.005	-0.032	***	0.005	0.190	***	0.018	0.012		0.030
IT	0.040	***	0.005	-0.023		0.014	-0.127	***	0.039	0.105	***	0.033
labour	0.334	***	0.005	0.365	***	0.006	0.225	***	0.028	0.259	***	0.031
intermediate inputs	0.755	***	0.005	0.740	***	0.005	0.398	***	0.031	0.782	***	0.026
intellectual properties	-0.007	***	0.003	0.112	***	0.012	0.008		0.019	-0.048	***	0.012
economic competencies	-0.039	***	0.006	-0.109	***	0.012	0.131	***	0.032	-0.055		0.034
computerized information	-0.038	***	0.004	-0.144	***	0.010	0.069	**	0.028	-0.033		0.020
competition	-1.173	***	0.019	-1.187	***	0.003						
interaction of IT with												
intellectual properties				-0.033	***	0.003						
economic competencies				0.013	***	0.003						
computerized information				0.029	***	0.039						
competition				0.020		0.013						

Table 7. Estimation results for SYS-GMM estimation (Blundell-Bond).

N = 396	Gross-output						Value added					
	coeff		se	coeff		se	coeff		se	coeff		se
non-IT capital	0.114	***	0.026	0.096	***	0.026	0.213	***	0.076	0.045		0.078
IT capital	0.116	***	0.009	0.112	***	0.033	0.047	**	0.020	0.049		0.082
labour	0.074	***	0.025	0.142	***	0.026	0.417	***	0.063	0.551	***	0.079
intermediate inputs	0.754	***	0.025	0.734	***	0.022						
intellectual property	0.037	***	0.014	-0.010		0.016	0.027		0.045	0.078	*	0.047
economic competencies	-0.054	**	0.021	0.109	***	0.029	0.030		0.051	0.154	**	0.071
computerized information	0.002		0.004	-0.019		0.012	0.041	***	0.011	-0.033		0.026
IT capital x IP				0.015	***	0.004				0.002		0.013
IT capital x EC				-0.029	***	0.005				0.034	***	0.011
IT capital x CI				0.009	***	0.005				0.033	***	0.011

Table 8. Estimation results for Ackerberg-Caves-Frazier method.

	Unobserved productivity is a first-order Markov process						Unobserved productivity is not a first-order Markov process		
N = 396	coeff		se	Coeff		se	coeff		se
non-IT capital	0.943		2.048	0.445	***	0.017	0.441	***	0.026
IT capital	0.627		1.067	0.050	*	0.027	0.146	***	0.026
labour	-2.814		1.916	0.411	***	0.027	0.468	***	0.170
intellectual property	0.018	**	0.008	-0.108	***	0.018	0.261	***	0.057
economic competencies	0.006		0.015	0.176	***	0.022	0.003		0.079
computerized information	-0.007		0.011	-0.033		0.023	-0.183	***	0.069
IT capital x IP							-0.103	***	0.016
IT capital x EC							0.036	**	0.017
IT capital x CI							0.039	**	0.018