ICT and Economic growth

Statistics Netherlands

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Explanation of symbols

.	Data not available
*	Provisional figure
**	Revised provisional figure (but not definite)
x	Publication prohibited (confidential figure)
–	Nil
–	(Between two figures) inclusive
0 (0.0)	Less than half of unit concerned
empty cell	Not applicable
2014–2015	2014 to 2015 inclusive
2014/2015	Average for 2014 to 2015 inclusive
2014/'15	Crop year, financial year, school year, etc., beginning in 2014 and ending in 2015
2012/'13–2014/'15	Crop year, financial year, etc., 2012/'13 to 2014/'15 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

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Foreword

Economic growth can be seen as the basis of our material well-being. Our present-day wealth is in essence the accumulation of growth in the past. While growth can be realised by increasing labour efforts and the use of capital goods, it is in turn mainly determined by innovation, increased productivity, and the efficiency with which goods and services are produced. Because demographic growth is slow, and there is great pressure on prices due to international competition, increasing efficiency by improving the production process and organization is key to maintaining competitiveness and ultimately our prosperity. Growth can also be achieved through the creation of new or improved products and associated markets.

The importance of innovation and productivity puts knowledge and technology at the heart of the policy debate. Many national and international policy initiatives focus on ways to improve knowledge generation and sharing, and on the creation and diffusion of new technologies. ICT has a special place in this debate, as it is an ever-renewing technology that has the potential to increase efficiency, facilitate knowledge sharing and enhance innovation.

In the light of this on-going political and academic debate, the Dutch Ministry of Economic Affairs commissioned and financed a project carried out at Statistics Netherlands, aimed at exploring the determinants of economic growth and productivity with a special focus on ICT and its interactions with other determinants. The result of this three-year study is before you. In this special publication, the research findings on the various themes are bundled. It includes studies at the industry level, firm-level data, and explorations of the determinants of economic performance together with the measurement of relevant phenomena.

Roughly, the determinants of productivity and economic growth can be categorised into two main categories: factors a firm can control – such as the level of employment or other inputs, and external factors over which firms have little or no control such as competition, globalisation and institutional factors. Moreover, aggregate growth is a result of the dynamics at the firm level. The chapters in this publication are all centred around these themes.
While the chapters each provide new and relevant information in the current political and academic debate on economic growth, they may be read individually or in concert, so that the reader can decide to focus on the topics of his or her own interest.
I hope you will find this publication relevant for the work in your area, or worthwhile for your own personal interest.

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Contents

1. Determinants of economic growth and productivity

In this introductory chapter, we will review the determinants of economic growth and productivity we found in the literature. Three categories are distinguished: within-firm determinants, external factors, and the dynamic process that determines how developments at lower levels of aggregation translate into changes at higher levels. We will present a general framework for analysis and provide illustrations with industry data, focusing on ICT and intangible capital.

1.1 Introduction

Past economic growth is key to the material well-being of people today. It therefore features prominently in economic policy, and there has been a long tradition yielding a vast amount of research about its determinants. Despite known shortcomings, economic growth is usually measured by growth in the gross domestic product (GDP). Mathematically, growth in the volume of total production – which is how GDP growth can be interpreted – can be broken down into two components, namely growth in labour and in labour productivity. In the face of ageing populations and increasing national and international competition, the latter component has become crucially important and the focal point of policy interest (e.g. Gelauff et al. 2004). Although ultimately interested in economic growth, the lion's share of the literature focuses on productivity. Labour productivity itself can be attributed to increases in capital intensity and to the efficiency with which capital and labour are combined in the production process, referred to as total factor or, more modestly, multifactor productivity.

The ICT and Economic Growth project, commissioned by the Dutch Ministry of Economic Affairs and carried out by Statistics Netherlands, aimed to shed light on the determinants of economic growth in the Netherlands. Its main research question was to investigate what the most important determinants of economic growth are with the focus on the role of Information and Communication Technology (ICT). Since the mid-nineties there has been a surge in scientific interest about the role of ICT in explaining the economic performance of the United States versus the European Union. A complementary body of micro-economic research has explored whether ICT can explain differences in the performance of firms.

Another aim was to investigate how different components are related. Again the focus was on the indirect effect of ICT on productivity via its impact on other factors, in line with its nature of General Purpose Technology (GPT). ICT not only contributes directly to a firm's production as a part of its capital stock, it also affects a firm's innovative capacity and its flexibility to adjust to economic shocks. Moreover, there is mounting evidence of the need to complement ICT investment with organisational changes and appropriate skills.

The current chapter has three purposes.
First, based on our study of the literature, we will review the main determinants of productivity growth, which are broken down into three categories. We will discuss the role of ICT in each category and highlight some empirical findings from the literature, following topics set out in leading overviews.
Secondly, we will sketch a general framework that illustrates how to measure productivity and various approaches to determine the impact of the various determinants in that framework.

Thirdly, by way of illustration we will provide an empirical analysis of productivity growth in the Dutch commercial sector. It is based on industry data from the Dutch growth accounts supplemented by data on intangible assets from the Knowledge module. We investigated the impact of ICT and intangibles and the possible complementarity between the two, and suggest directions for follow-up research.
The next three sections are devoted to each individual aim. Then we summarise and a take a peek inside the chapters ahead.

1.2 Overview of determinants

Based on our reading of the literature we distinguished three broad categories of determinants of economic and 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.

We will discuss the relevant determinants of each and where applicable the role of ICT. Moreover, we will briefly review some of the empirical findings on how each variable relates to productivity. In the next section, after discussing a general framework for analysis, we will also dwell on the impact of growth and productivity of these determinants.
Due to limitations of space and time, this overview does not do full justice to all topics or the works cited. However, we hope to sketch a rough picture of relevant issues, after which subsequent chapters will deal with selected topics in more detail.

Input variables in the production process of a firm

Capital and labour

The first group of determinants can essentially be characterised as variables over which the firm has some form of control, i.e. they are the firm's choice variables (hence sometimes called decision or control variables). Within this group we distinguish between capital and labour.[1)] The main issue is to distinguish between different types of these inputs. Then there is the other input into the production process: knowledge. As this is difficult to attribute to one of the primary factors of production, it constitutes a production factor in itself. In this section we will first discuss capital, labour and knowledge as input into the production process. Then we will discuss the role of ICT and review some of the empirical work in these areas.

Starting with capital inputs, it is not uncommon in productivity research to treat them as a single homogeneous input, mainly because of analytical convenience and a lack of data

1) We will restrict ourselves to the value added model of production, hence ignoring intermediate inputs. In general, there is less literature on the relation between productivity and intermediate inputs than on capital and labour. That is not to say that the issue is uninteresting. For example, there may be interesting policy implications from research showing that firms that innovate to increase their energy efficiency, become more competitive (Van Leeuwen and Mohnen, 2013).

on separate types of capital. This analytical simplification assumes that one can aggregate over different types of capital.[2)] Because of its durable character, the costs of using capital are not equal to the investment in capital goods. The preferred measure of capital input is therefore its user cost (e.g. OECD, 2001), which accounts for depreciation, revaluation and opportunity costs. Typically, such measures can be constructed for industries or the total economy but not for firms due to the lack of capital surveys or long investment series and detailed information on depreciation.
The focus on capital as homogeneous input can be restrictive as returns to capital investment can be very different for different types of assets. As exemplified by the growth-accounting literature, there is an important distinction between ICT and non-ICT capital. ICT is recognised as a special part of capital, with different features from other types of tangible capital. ICT capital itself consists of computers, software, and telecom equipment. Non-ICT capital is an aggregate of buildings, structures, and non-ICT equipment.
Labour is likewise often considered a homogenous production factor in empirical productivity analyses. However, there are many worker characteristics that can cause variation in their productivity, such as education, tenure, gender, age, and type of contract (part-time vs. full-time, temporary vs. tenured). Again, considering all workers as a homogeneous group is restrictive.

Knowledge-based capital

In the recent literature on productivity and economic growth, it is also increasingly recognised that knowledge is a productive asset. Knowledge creation includes human capital in the form of education and training, research, market development and organisational and managerial efficiency, see Corrado et al. (2012) amongst others. This study recognises that Europe and the USA "arguably have their greatest comparative advantage". In fact, knowledge should be seen as a form of capital, as firms invest in the knowledge generation and build up a "knowledge stock" with similar features as tangible capital. A widely adopted model in this respect is that of Corrado, Hulten and Sichel (CHS, 2005), who capitalised knowledge-based assets, distinguishing between computerised information, economic competencies, and firm-specific human capital. Computerised information includes software and databases, so ICT capital can partly be seen as physical capital (hardware and telecommunication equipment), and partly as intangible (software and database).[3)]

Moreover, knowledge and skills of workers form a key factor, often captured in the share of highly educated workers. One could argue whether this is part of knowledge capital or a refinement of labour input. A useful distinction may be the difference between the prior education of workers and the investment in training made by a firm, which is often firm-specific. Moreover, it is possible to distinguish between different types of training, such as investments in ICT-related training.

2) Fisher (1965) discusses the economic assumptions one needs to make when aggregating different types of capital; see also Wilson (2009).

3) Within recent academic and policy debates the 'Big Data' phenomenon has received a great deal of attention. However, as is common with new phenomena, the notion of big data is not yet clearly defined. It comprises investment in large databases, the ability to analyse these data, and to put it to use in the creation of business value. So far the information on this topic is scarce. Statistical agencies are beginning to explore the opportunities offered by big data (traffic, mobile usage, social media feeds) in the production of statistics. Using data from a private survey , Brynjolfsson et al. (2011) report that firms involved in data-driven decision making (which entails the use of Enterprise Resource Planning, Supply Chain Management, and Customer Resource Management, in combination with the use of Business Intelligence Systems), are about 5 percent more productive than other firms with similar ICT endowments.

The role of ICT for input-related determinants of productivity

The discussion above shows that ICT's role with respect to the input-related determinants of productivity is twofold. First, ICT capital itself is a production input. There is a large variety in types of ICT, tangible (i.e. hardware) and intangible (i.e. software). Secondly, ICT is arguably complementary to other production factors, in particular to knowledge, innovation and worker skills. Technology may be used more effectively by skilled than by unskilled workers, while skilled workers become more effective with better technology. For example, one of the CHS knowledge-based assets is organisational capital. Such organisational capital can benefit from the availability of ICT, while creating business value from ICT investment requires a suitable organisational environment or organisational change. Moreover, ICT developments such as online purchasing and selling 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 (Shapiro and Varian, 1998). ICT is also seen as an enabling technology that helps in generating and sharing knowledge (Jovanovic and Rousseau, 2005). So ICT enables innovation and helps to diffuse it.

Review of empirical findings on input-related determinants

In this section, we will highlight some findings from the empirical literature on the relationship between the various inputs into production and productivity. We will start with capital, largely focussing on ICT capital, and then move on to labour and knowledge, and possible complementarities between the various inputs.

A stylised fact from the empirical macro-literature is that the United States has seen higher productivity growth in the last two decades than the European Union (see e.g. Van Ark et al. 2008). While institutional differences such as more flexible labour markets and more market competition in the USA may explain some of these differences, international benchmarking exercises in growth accounting suggest that the USA-EU differences are best explained by the rise of the knowledge economy. As demonstrated by Jorgenson et al. (2008), the surge in productivity in the second half of the nineties was driven by the high performance of the ICT-producing sectors, whereas aggregate productivity growth at the start of this century was largely determined by growth among heavy ICT users such as retail, trade and financial services. Jorgenson et al. concluded that the developments in the ICT sectors and investments in ICT enabled the creation of innovative business processes. The growth accounting literature has yielded insights that showed that the familiar Solow (1987) productivity paradox ("We can see ICT everywhere but in productivity statistics") no longer holds: ICT is by now clearly visible in the productivity figures.

Despite these valuable findings, there are several caveats to be made. First, 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. The advent of new forms of ICT seems to have increased heterogeneity in performance, even among firms with similar ways of 'doing' IT. Secondly, by definition growth accounting is about decomposing high-level developments into parts. Although this has proved to be a powerful tool, the results do not imply causality. To unravel the causal relationship between productivity growth and its potential drivers, we need to resort to econometric techniques. However, the identification of an effect of ICT on productivity growth tends to be more difficult when we use the same growth accounting industry and country data for regression-based analysis, especially when attempting to control for econometric problems such as unobserved heterogeneity and endogeneity (Stiroh, 2005; Draca et al. 2006). In the light of these identification issues and the micro-level heterogeneity mentioned above, many studies have shifted the focus to firm-level data.

In their often cited study Brynjolfsson and Hitt (2000) point out that ICT positively affects firm performance, but that the business value generated by ICT is largely determined by how it is used. Complementary organisational changes in business processes and work practices form the basis of productivity growth. In turn, these changes also enable firms to develop new or improved products and services. Investments in ICT complement changes in other aspects of the organisation as ICT helps to reduce communication costs and facilitate monitoring. The use of ICT can lead to more efficient decisionmaking and to a flatter, decentralised organisation structure with greater worker responsibility. Moreover, with respect to a firm's external relations, ICT reduces the benefits to vertical integration and creates the opportunity to rely on specialised outside suppliers. ICT makes it possible to reorganise the production structure to increase consumer benefits in terms of timeliness, customisation and new complementary services. Empirical evidence for the existence of complementarities between workplace practices, organisational change and ICT is documented in a vast literature consisting of case studies and firm-level econometric work. Examples include Ichinowski et al. (1997), Black and Lynch (2001), Crespi et al. (2007), and Bloom et al. (2012). The enabling function of ICT in innovation is confirmed by Spiezia (2011), who presented evidence from a cross-country firm-level project. So ICT also contributes indirectly to growth through innovation.

Turning to labour inputs, Sianesi and Van Reenen (2003) presented an extensive survey of the role of human capital in growth, i.e. a highly skilled workforce is associated with higher growth and productivity. However, in contrast to early endogenous growth models, they found that the return to education diminishes over time. In addition, complementarities play a key role in the effect of human capital. For example, a firm is able to invest in R&D and knowledge-intensive capital because of highly skilled staff. Caroli and Van Reenen (2001) found that organisational change has more impact on productivity in firms with highly skilled workers and that the complementarity between ICT and organisational innovation disappears when skills are taken into account. Bartel et al. (2007) found that firms increase their demand for skilled workers when they invest in ICT, which is in line with the overall evidence on skill-biased technological change. Arvanitis (2005) found that human capital and ICT in Switzerland contribute positively to productivity, and produced evidence for complementarity, but not with organisational change. There is a summary of various articles on the productivity effects of human capital, organisational change and ICT, showing that results vary per setting. Hagsten and Sabadash (2014) presented cross-country micro-level evidence from various European countries supporting the view that human capital complements ICT, especially technical education (which they loosely referred to as ICT-related human capital).

The quantification of the contribution of knowledge to economic growth is relatively recent. This has been done in various countries, based on the framework by Corrado, Hulten and Sichel (CHS). In the USA, 27 percent of labour productivity can be attributed to investments in the knowledge capital categories distinguished in the CHS framework. In Europe this averages 20 to 25 percent, and in the Netherlands 22 percent (see Corrado et al. 2012). A larger share is still due to TFP growth: about 30 percent in the USA, 42 percent in Europe and 43 percent in the Netherlands. Corrado et al. (2014) used cross-country data on intangibles and ICT, and found that the returns of ICT are higher when complemented by intangibles. Moreover, the returns to non-R&D intangible capital is higher than its cost share, suggesting the existence of spillovers. Likewise, using cross-country industry-level data, Chen et al. (2014) found that intangible capital is more productive in ICT-intensive industries. These results clearly underline the complementary nature of ICT and knowledge-based assets.

In the micro-economic literature the working horse model with respect to the productivity effects of R&D and innovation is the so-called CDM model, after Crépon, Duguet and Mairesse (1998). This model consists of three equations reflecting stages in the route from investment in innovation to effect on firm performance: firms invest in R&D, which leads to innovation via a so-called knowledge performance equation (Griliches and Pakes, 1984), and ultimately, this knowledge feeds into a separate performance equation. Accounting for selectivity issues (as not every firm invests in R&D), and endogeneity issues around R&D and innovation, Crépon et al. found a significant effect of product innovation on productivity. Many studies have performed analyses in the spirit of the CDM model, and corroborated the results, see e.g. Van Leeuwen and Klomp (2006) for the Netherlands and Lööf and Heshmati (2006) for Sweden. Most studies also confirm a positive effect of R&D on innovation output, although the elasticity varies. The same holds true for the effect of (product) innovation on productivity.

Griffith et al. (2006) have extended the knowledge production function to include both product and process innovation, but found that process innovation has less impact on productivity. In a study for the Netherlands, Polder et al. (2010a) presented evidence that both R&D and ICT positively affect the probability of innovation, but that R&D is important for innovation in manufacturing only, not in services. The study distinguished product, process, and organisational innovation, and found strong evidence that organisational innovation has the strongest productivity effects. Product and process innovation contribute to higher productivity but only in combination with organisational innovation. This can be interpreted as evidence for complementarity among different types of innovation.

The business environment

The environment in which a firm operates influences its behaviour. Syverson (2011) calls this the "external drivers" of productivity. From our literature study and Syverson's overview, we gathered that the most prominent environmental factors are the regulatory, policy and institutional environment, competition in product markets, and knowledge spillovers and externalities. Environmental factors largely determine the responsiveness of firm performance to exogenous shocks and the entry/exit process. They are the drivers of productivity beyond the direct control of firms. They are also most strongly linked to policy instruments as levers to pull for policy makers in order to influence firm behaviour. Again we will discuss various determinants under these groups, the role of and relation to ICT and findings from the empirical literature.

Regulatory, policy and institutional environments

A firm operates within a set of rules posed by national laws and regulations. Its labour policy is subject to labour market regulation (LMR), its market to product market regulation (PMR), and its production process to environmental regulations. These conditions largely determine the firm's actions. Moreover, in order to be able to produce effectively, the availability and flexibility of the relevant inputs is vital. Institutional features such as the education system, the role of unions, the structure of the financial sector, and labour market conditions are crucial. For example, the flip side of the positive association of human capital with growth discussed above is that a shortage in the labour market of qualified labour can be detrimental. If access to finance is also restricted, businesses are hampered in realising their investment opportunities.

Competition in the product market

Competition in the product market can arise from potential entry, price competition among incumbents in the national market, as well as from trade-induced pressures. It affects productivity in at least two ways. It weeds out poorly performing firms because the market will punish inefficiency (see e.g. Boone, 2000). The resulting dynamics form an important determinant of productivity. These will be discussed in the next section. 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 was pointed out by Aghion et al. (2005). There may be a turning point in the effect of increasing competition. If firms are under too much competitive pressure they cannot invest in longer-term productivity-enhancing innovation. So it is a policy challenge to find a balance between competition, and for example the protection of intellectual property rights (see e.g. Van Der Wiel, 2010).

Spillovers and externalities

A firm's productivity level can also be affected by the actions and practices of others. Besides competition in the product market, this involves spillovers and externalities that are closely linked to the knowledge-based determinants. The fact that knowledge is mostly non-rival and non-appropriable suggests there can be knowledge spillovers between firms.[4)] That is, firms can learn from each other about best-practice technology, ICT use and R&D. Moreover, there may be network effects from the use of technology by other firms, as it increases the value of adoption. In this sense, 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 linkages between firms).

The issue of spillovers and externalities raises interesting policy issues, in that the social benefits are higher than the private benefits. The risk is that the optimal investment level for firms is below the optimal level from an aggregate point of view. This motivates the use of subsidies or tax incentives for R&D. A drawback, however, is that these can also decrease the level of competition. In general, tax incentives or subsidies are justified when the market fails to deliver an overall long-term optimal outcome.

Internationalisation and global value chains

A last external factor is the internationalisation of trade. Increasingly, production takes place in a globalised world (Timmer et al., 2014). The increased market size and trade affect the intensity of competition. Much in the same way as we discussed with competition, increasing internationalisation leads to lower mark-ups and greater pressure to increase productivity. Trade will force the least productive firms out of the market and reallocate market shares towards the more productive exporting firms (Melitz and Ottaviano, 2008). If trade is costly, however, this may not be the best selection process, especially when costs are asymmetric between trading partners.

ICT and the role of external drivers of growth

In general, strict regulations or "red tape" may hamper the flexibility of firms and are therefore bad for productivity. In this respect ICT-intensive firms may be more flexible, and firms that rely more on ICT can cope more easily with changes in the regulatory environment.

4) Not all sorts of knowledge are subject to spillovers, however, for example brand equity and firm-specific human capital are in fact highly excludable (OECD, 2012).

Moreover, ICT has changed the nature of competition (Brynjolfsson en Saunders, 2010). It affects the ways in which firms produce, gather information and communicate with customers, suppliers, and competitors. Firms that use ICT can effectively escape competition and achieve greater profitability through more efficient production, better information on market developments and the flexibility to react to them. Moreover, given lower search cost and more transparency about quality and prices due to the internet, ICT has the potential to enhance market selection (Brynjolfsson and Smith, 2000). Profits tend to become more concentrated. In markets with homogeneous products, customers tend to seek out the highest quality product at the lowest price (although suppliers of inferior products can engage in price competition to attract customers).

The market for information goods itself is an extreme example of an industry where profits become concentrated. This is mainly because of the economies of scale (i.e. high fixed production costs and low or zero replication cost), and the existence of network externalities. Here we see a phenomenon known as Metcalfe's law, where using particular types of software or social media becomes more valuable as more people use it (see Shapiro and Varian (1998), and Brynjolfsson and McAfee (2014)). These network externalities also apply to communication equipment, see e.g. Corrado (2011). Policy in such cases has to draw a line between allowing standardisation and preventing anti-competitive behaviour. Moreover, firms may collaborate as products must be compatible, which is good for knowledge sharing but holds a risk of collusion.

Competition can also be a driver to adopt new technology while there may be feedback effects from competition to ICT adoption. In all, ICT and competition are key determinants of productivity, but while we can zoom in on specific aspects of the relation between the two, the overall picture is very complex.

ICT allows firms to gather and process information faster and more easily. The hypothesis is that ICT-using firms tend to gain earlier and greater benefits from spillovers. In digital markets or markets that rely heavily on ICT, the costs of copying or replication may be so low that the knowledge from spillovers can easily be capitalised (Brynjolfsson et al., 2008). The use of ICT itself, e.g. different types of e-business systems and e-commerce, may be subject to network effects, in the sense that the value of ICT (and hence the payoff to adoption) increases if the firm's suppliers and customers also use ICT.

The role of ICT in trade is at least twofold. Due to the advances in communication and the introduction of the internet and e-commerce it has become easier to buy and sell abroad. At the same time, production has become more fragmented over different producers. As ICT developments enhance communicating and monitoring over the entire production chain, it facilitates the outsourcing and offshoring of particular business functions.

Findings from the literature on external drivers of productivity

Bartelsman et al. (2011) found evidence that firms adopt a careful hiring policy under strict labour market regulations. Investments in ICT or other forms of capital may be hampered when they require hiring extra employees. In a recent extensive study for the UK Van Reenen et al. (2010) concluded that the key policy message is that strict product and labour market regulation (PMR and LMR) temper the positive impact of ICT on productivity growth. Firms under tight LMR and PMR regimes are restricted in their generation of business value from ICT. Then, the positive effect of ICT in reallocating production factors towards more productive units is hampered. Evidence for positive reallocation effects following a change in regulation is given by Olley and Pakes (1996) who found that aggregate productivity increased after deregulation in the USA Telecom sector. Evidence for a counterproductive measure was documented by Haskel and Sadun (2012), who detected a drop in average firm-level TFP in multi-store retail chains in the UK following a change in regulation that increased the cost of opening large stores.

Overall, the empirical evidence supports the view that competition fosters productivity growth, see e.g. Nickell (1996). Ahn (2002) provides an extensive overview of the literature, which confirms long-term positive effects of competition on innovation and productivity. Several studies performed and confirm the results of Nickell (1996) for the Netherlands, see e.g. Felsö et al. (2001) and Lever and Nieuwenhuijsen (1998). Polder et al. (2010b) found that increased competition first leads to a negative effect after which productivity rises. Firms need time to adjust, e.g. through R&D investment or through adjusting the production process, which may have a disruptive effect at first.

The evidence on the existence of spillovers from R&D goes back at least as far as Griliches (1979, 1992). Cincera (2005) found evidence for a positive effect of R&D spillovers on productivity for different ways of measuring such spillovers. Bloom et al. (2007) looked at the balance between the positive effect of knowledge spillovers and possibly negative market-stealing effects, and concluded that the positive effect dominates. Bartelsman et al. (2006) studied knowledge spillovers from the technological frontier and found that the national technological frontier has more impact on productivity growth of firms than the global frontier. Firms learn most from their domestic counterparts and the pull of the global frontier diminishes when the distance increases. Firms that are too far from the global frontier can no longer catch up. Consequently, an economy may be able to catch up if its national frontier is close to the global frontier, but otherwise it won't. The relevant policy question is where policies should be designed to push the technological frontier, and where growth can best be stimulated through catching up with the frontier. Van Der Wiel et al. (2008) concur that the national frontier is more important than the global frontier in the Netherlands. They also found major complementarities in that competition provides the incentive for and that R&D facilitates catching up on both frontiers. This is in line with the 'two faces of R&D' argument put forward by Griffith et al. (2004), who found evidence that firms require a basic level of R&D to be able to absorb knowledge spillovers from other firms.

Van Der Wiel and Van Leeuwen (2001, 2004) presented firm-level evidence that such 'ICT spillovers', or externalities, matter for the Netherlands. Mun and Nadiri (2002) also found that ICT externalities can explain substantial parts of TFP growth in the USA. However, Van Reenen et al. (2010) found no evidence of such productivity effects for the UK, although ICT adoption by neighbouring firms has a positive effect on adoption. In a recent study, Van Leeuwen and Polder (2013) found evidence for cross-country spillovers for adoption of e-business systems between firms in the same industry, but not between firms in different industries within the same country.

In the trade literature, the export decision and its intensity are found to be largely driven by a firm's comparative advantage in efficiency (Eaton et al., 2011). Pavcnik (2002) documented evidence of productivity increases for Chile due to reallocation and within-firm productivity increases after a trade liberalisation. De Loecker and Warzynski (2012) found that competition is fiercer for exporting firms.

Firm and industry dynamics underlying aggregate growth

Besides the determinants directly impacting on the performance of firms, aggregate growth is also determined by lower level changes. To understand aggregate growth, it is necessary to examine the dynamics of the composing parts of a pertinent aggregate, such as population changes and changes in the distribution of the variable of interest. We will discuss the aggregation from firms to industry (micro to meso), and from industries to the total economy (meso to macro), starting with the latter. As with the other determinants, we will sketch the potential role of ICT in this process and review some key findings from the literature.

Economic growth and industry growth

A country's GDP is the sum of the production in value added of all industries. The economic growth of a country in terms of GDP growth is determined by the real value added growth of the underlying industries. 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 represented in a so-called shift-share analysis (see e.g. Griliches and Regev, 1995, and 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 their relative size. In an efficient economy, production factors are allocated to the more productive industries.

Industry growth and business dynamics

In a similar vein, industry dynamics can be decomposed into the dynamics at the firm-level. Firms grow or contract just like industries do, but one must also take the contribution of attrition and new entry into account. Again, allocating production factors to the more productive units increases overall productivity. So in an efficient economy, low productivity firms are replaced by higher productivity firms. There is a strong link to competition here, which is the market force determining the entry, exit and allocation process.

The role of ICT in business and industry dynamics

The role of ICT in the dynamic process of allocation and selection is that it may increase the flexibility of firms and as such their ability to cope with economic shocks, increasing relative productivity and chances of survival. ICT can be a major factor in determining the winners in the competitive process of reallocation and exit. Moreover, one can distinguish between ICT producing, ICT intensive and less ICT intensive industries. They may display different growth patterns and their evolution over time determines overall growth. Whether the impact of ICT on aggregate employment growth is also positive is not clear a priori. ICT is believed to increase productivity, and ICT-related industries may create new jobs through higher growth, but new technologies may take over some tasks rendering certain jobs obsolete. It is not settled what the balance is between those two forces (e.g. Brynjolfsson and McAfee, 2011). The policy challenge is to accommodate the flexibility needed on the labour market to let workers flow from obsolete to promising jobs.

Findings from the literature on firm and industry dynamics

The productivity gap between the USA and the EU is usually attributed to a smaller ICT industry in the EU and less growth of its ICT-using industries. Using a shift-share analysis, Van Ark et al. (2003) found that most of this difference is caused by the fact that ICT-using industries in the EU lag behind.

One conclusion in the survey article by Pilat (2004) is that there is a lot of experimentation going on in an ICT-driven economy, where some firms succeed and grow, and other firms do not and exit. A recurrent finding in the empirical literature is that such business dynamics, especially the process of reallocation, are a major source of aggregate productivity growth (Bartelsman and Doms, 2000; Foster et al., 2002). To seize the benefits of ICT, policy should create a business environment that cushions this process of creative destruction. The evidence also suggests the necessity of simultaneously analysing firm-level and aggregate developments if one is interested in the sources of economic growth.

Balk and Hoogenboom (2003) found for the Netherlands that the decomposition used matters for the conclusions about what the key component in aggregate growth is. Foster et al. (2001) corroborate this conclusion in their review of the literature, but they also found that the importance of entry is a robust finding in the empirical literature. Foster et al. (2002) found that much of the productivity growth in USA services is explained by new entrants replacing less productive exiting firms.

ICT-intensive markets face more turmoil: the productivity spread is higher and there is a higher turnover of firms in terms of entry and exit (OECD, 2012). The ICT intensive industries tend to be riskier, but in the end aggregate productivity is higher as high-productivity firms survive and low-productivity firms are replaced by innovative and more productive new entrants. The other side of the coin is that profits tend to become more concentrated, with consequences for the distribution of welfare (Brynjolfsson and McAfee, 2014).

Concluding remarks on the literature review

Our discussion of the literature is necessarily brief due to the limitations of space and time. We just scratched the surface of most topics and left out several quite interesting other ones. Each subtheme could be the topic of a literature review in itself of book-like rather than chapter-like proportions. In the subsequent chapters several topics are explored in greater detail.

Our overall impression is that, although unified by a common search for explaining productivity growth at different levels of aggregation, there is no encompassing framework in which all determinants can be gathered simultaneously. What one branch of the literature considers crucial may be explicitly or implicitly assumed away in another branch for reasons of analytical convenience. However, most of the literature centres around the augmented production function as a common approach to assessing productivity effects. We will discuss such a framework in the next section, and highlight how the determinants discussed can be analysed.

1.3 Framework for analysis

General model and estimation issues

A general production function can be defined as

$$Y_{jt} = A_{jt}F(X_{jt};\theta_{jt}) \quad (1)$$

where Y_{jt} is the output of industry j and time t, produced with the factors of production gathered in the vector X_{jt}. The production technology is captured by a function F(), subject to the technology parameters θ_{jt}, which can in theory be different for each industry and vary over time. Even if the structural parameters are the same over industry and time, the output generated with the same amount of inputs may vary, reflected by the scaling factor A_{jt}, which is usually referred to as (total factor) productivity, or TFP.[5)]

To calculate productivity, the researcher now has a variety of choices. If one is not interested in determining the effects of the inputs on outputs, one can settle for an index approach. This usually involves the calculation of the change in productivity, or a comparison of the productivity of a unit with respect to a certain benchmark. In terms of a relative change in productivity for example, we can write

$$\frac{A_{jt}}{A_{jt-1}} = \frac{Y_{jt}}{Y_{jt-1}} / \frac{F_{jt}}{F_{jt-1}} \quad (2)$$

or , in terms of log growth we can write

$$\Delta \ln A_{jt} = \Delta \ln Y_{jt} - \Delta \ln F(X_{jt};\theta_{jt}) = \ln\left(\frac{Y_{jt}}{Y_{jt-1}} / \frac{F_{jt}}{F_{jt-1}}\right) \quad (3)$$

where all variables are valued in prices of the same year.
The crucial matter is the choice of the function F, the index that weighs together the inputs to a measure of total inputs, using weights θ_{jt}. For example, F can be chosen to be a linear function of the inputs

$$\frac{F_{jt}}{F_{jt-1}} = \theta_{jt}^{K}\frac{K_{jt}}{K_{jt-1}} + \theta_{jt}^{L}\frac{L_{jt}}{L_{jt-1}} \quad (4)$$

where weights are equal to the share of the inputs in total production costs.[6)] A popular choice in the economic literature is the Cobb-Douglas function. Considering value added as our output measure, the loglinear form is

$$\ln VA_{jt} = \ln A_{jt} + \theta_{jt}^{K}\ln K_{jt} + \theta_{jt}^{L}\ln L_{jt} = \theta_{jt}^{K}\ln K_{jt} + \theta_{jt}^{L}\ln L_{jt} + \mu_{jt} \quad (5)$$

where *VA* is value added, and *K* and *L* are capital and labour services.

5) Our formulation leaves out various further complications. We assume that output can be expressed as a single homogeneous variable. The technology parameter is 'Hicks neutral', meaning that when the structural parameters are the same, the only source of productivity differences is the scaling factor, which is assumed to be separable from the production technology function.

6) Here various choices are available: for example, choosing the shares in cost in year *t* leads to a Paasche index, cost shares in year *t*-1 leads to a Laspeyres index.

Cost shares are sometimes assumed to be equal to the output elasticities of the inputs. However, these elasticities can also be determined econometrically. Deviations of the elasticities from cost shares are usually interpreted as evidence that the restrictive assumptions needed for cost shares to be equal to elasticities do not hold. This may be due to imperfect competition, returns to scale, adjustment costs, or spillover effects. Estimation of (5) with time-series or panel data on the value of output and inputs requires transforming all variables to real terms (i.e. in prices of a particular base year). Usually this is done with the help of industry input and output deflators. This makes them comparable over time and makes changes interpretable as volume changes.[7] It leads to an estimate of so-called 'revenue TFP', as opposed to 'physical TFP' which is determined on the basis of data about actual volumes of output and inputs (see Foster et al. 2008). While the latter measure is to be preferred with an eye on heterogeneity in prices within industry and between products, data restrictions have led researchers to focus on TFP based on revenue measures.

For expositional clarity, we will assume for the moment that capital is homogeneous and there are no intangibles. The $\ln A_{jt} \equiv \mu_{jt}$ term captures differences in productivity between industries and over time. The statistical properties of this disturbance term determine the appropriate way to estimate (5). Ordinary Least Squares (OLS) estimation of may lead to biased estimates because of the endogeneity of the choice of the level of production factors with respect to unobserved productivity. If firms have information on their productivity at the time of choosing their input levels that the econometrician has not, the unobserved productivity level is contained in the disturbance μ_{jt}. Then the choice of the level of the production factors $X_{jt} = \{K_{jt}, L_{jt}\}$ will be correlated with the overall error term μ_{jt}, which means that they are endogenous (i.e. technically, $E[X_{jt}\mu_{jt}] \neq 0$). One finds various methods to account for this endogeneity of inputs in the literature, see e.g. Griliches and Mairesse (1995), Arellano and Honoré (2001), and Ackerberg et al. (2006) for overviews. There are two main approaches within the current 'state-of-the art'. There is the 'Dynamic Panel Data (DPD)' approach, in the spirit of Arellano and Bond (1991), and developed further by Arellano and Bover (1995) and Blundell and Bond (1998, 2000) among others. And there is the 'structural' or 'control function' approach as advocated by Olley and Pakes (1996) and Levinsohn and Petrin (2003), and more recently extended by Ackerberg, Caves and Frazier (2006). The assumptions underlying both types of estimators are similar. We will focus on the Blundell-Bond, or 'System-GMM' estimator. Comparing different estimation strategies, Stiroh (2005) prefers this approach to OLS and other familiar panel data estimators such as first-differences and fixed effects. See Dobbelaere and Mairesse (2013) for a recent application of this method to production functions.

The panel data model distinguishes different components in the disturbance term. Firstly, ω_{jt} is thought of as the productivity state that is observed by the firm but not by the researcher. It may include managerial capability, expectations about the state of the machinery or workers, et cetera (Ackerberg et al. 2006). The information about ω_{jt} is used to set the levels of X_{jt} , which is the source of the endogeneity problem. Secondly, there is a component which is also unobserved for the firm, u_{jt}, and therefore uncorrelated to X_{jt}. This component may include the weather, uncertainty about policy changes, actions by competitors, et cetera. Allowing also for an industry-specific component λ_j (capturing average productivity

[7] This is a tricky difference with the index approach, where current variables are usually valued in prices of the previous year rather than a common base year, due to the loss of additivity in the input index when using the latter approach, see Balk and Reich, (2008).

by industry, as well as any industry-specific measurement error), we have the overall disturbance

$$\mu_{jt} = \lambda_j + \omega_{jt} + u_{jt} \tag{6}$$

Differencing (5) gets rid of λ_j but does not help to eliminate ω_{jt}, unless $\omega_{jt} = \omega_j$, i.e. the productivity state does not change over time. Both the SYS-GMM and the control function approach assume that ω_{jt} follows a first-order autoregressive process (AR(1)), i.e.

$$\omega_{jt} = \rho\omega_{jt-1} + e_{jt} \tag{7}$$

where $\rho < 1$ and e_{jt} is white noise. The economic interpretation of the AR(1) process for the unobserved productivity component could be that firms base their expectations in part on the historical productivity state.
Denoting variables in logs in small case, and using (7), we can rewrite (5) as

$$va_{jt} = \pi_1 k_{jt} + \pi_2 k_{jt-1} + \pi_3 l_{jt} + \pi_4 l_{jt-1} + \pi_5 va_{jt-1} + \lambda_j^* + w_{jt} \tag{8}$$

where $w_{jt} = e_{jt} + u_{jt} + \rho u_{jt-1}$, and $\lambda_j^* = (1-\rho)\lambda_j$
The π's are reduced form parameters that relate to the structural parameters as $\pi_5 = \rho$, $\pi_1 = \theta^K$, $\pi_2 = -\rho\theta$, $\pi_3 = \theta^L$, and $\pi_4 = -\rho\theta^L$. Note that this is a dynamic model (i.e. there is a lagged dependent variable on the right-hand side) with a fixed effect λ_j^*. Differencing removes the fixed effect:

$$\Delta va_{jt} = \pi_1 \Delta k_{jt} + \pi_2 \Delta k_{jt-1} + \pi_3 \Delta l_{jt} + \pi_4 \Delta l_{jt-1} + \pi_5 \Delta va_{jt-1} + \Delta w_{jt} \tag{9}$$

This equation can be estimated using the moment conditions[8)]

$$E\left[x_{jt-s}\Delta w_{jt}\right] = 0 \tag{10}$$

where $x = \{k, l, va\}$, and for $s \geq 2$ or $s \geq 3$ depending on serial correlation of the disturbance.
A Generalized Method of Moments (GMM) estimator 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 a large finite sample bias and poor precision when the lagged levels are weak instruments for the differenced variables. Blundell and Bond (1998) therefore suggest to estimate equations (8) and (9) simultaneously, extending the set of moment restrictions with lagged differences for the level equation (8). Assuming that differences in x are unrelated to the fixed effect,

$$E\left[\Delta x_{jt-s}(\lambda_j^* + w_{jt})\right] = 0 \tag{11}$$

for $s = 1$ or 2, again depending on serially correlated disturbances or not (and moments for larger s's can be shown to be redundant). The complete set of moment restrictions is used to obtain a GMM estimation of the reduced form parameters. The output elasticities θ^X can be backed out using a Minimum Distance procedure, noting that $\pi_5 = \rho$, $\pi_1 = \theta^K$, $\pi_2 = -\rho\theta^K$, $\pi_3 = \theta^L$, and $\pi_4 = -\rho\theta^L$ (see e.g. Wooldridge, 2002).

8) The validity of these moment restrictions requires some additional assumptions on the initial conditions.

Analysis of the determinants in the framework

In this section we will discuss the analysis of the determinants of economic growth and productivity identified in the review of the literature in the previous section.

Heterogeneous inputs and knowledge capital

In the framework above, the refinement of capital can be seen 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 individual input one can estimate its contribution to productivity growth and/or its elasticity. Ideally, one should use the user cost of capital but various proxies are common, including capital stock calculated from time-series on investment, book values, and data on depreciation.

Depending on the data at hand, labour input is typically measured by the headcount of workers, full-time equivalents, hours worked, or real wages. The refinement of labour can be seen as the introduction of various types labour in each of these measures, represented in a vector $L = (L_1, L_2, ..., L_n)$. For each of these separate types one can estimate its contribution to productivity growth and/or its elasticity by using one of the volume measures. Alternatively, in a growth-accounting framework, a possibility is to use a quality-adjusted price index for labour cost, (see chapter 2). In this case, the contribution of labour to economic growth can be broken down into a component related to the volume change (i.e. hours worked) and a composition effect.

In a growth-accounting type framework, knowledge can be capitalised and added to the capital services used by firms. Essentially it then becomes part of the vector of capital inputs *K*. Industry output and the use of intermediate goods then need to be adjusted, because one should take into account the knowledge production as a type of output. In addition knowledge investments are typically included in categories of intermediate inputs in the traditional framework. For example, cost of training comes under services. Statistics Netherlands has constructed time-series of knowledge capital along the lines of Corrado et al. (2005), see Van Rooijen et al. (2008). The resulting data also allow the econometric estimation of industry-level production functions, as in Corrado et al. (2014) and Chen et al. (2014).
In the micro-economic literature, knowledge usually enters through the parameterisation of the productivity term (i.e. the parameter *A* in the production function), notably following the work by Griliches (1979) and Crépon, Duguet and Mairesse (1998, the ‘CDM’ model):

$$A = f(KNOW) \tag{12}$$

where *KNOW* can be thought of as a vector of knowledge related inputs. One can substitute $f(\cdot)$ for *A* in the production function and estimate the contribution of knowledge directly, or one can first estimate productivity using cost shares, and relate productivity to knowledge in a second step. Examples of knowledge variables to be included in the model are R&D intensity or innovative activities. One can distinguish further between different types of innovation, such as technological and non-technological innovation. Measuring innovation, however, can be tricky, and studies usually rely on subjective firm-level surveys or patent information. Non-technological innovations like organisational and management practices are especially hard to measure, although there is evidence that such investments make or break successful enterprises (Bloom et al., 2012).
Complementarities can be analysed in the production function framework by adding relevant cross-terms. Finally, the enabling effect of ICT may be captured further by an

additional equation that determines knowledge as a function of ICT:

$$KNOW = f(ICT) \tag{13}$$

as in Van Leeuwen (2008) and Polder et al. (2010a).

External drivers of productivity

Assessing the impact 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, with preferably some variation over other dimensions such as industries or size classes. One can estimate the productivity within countries by applying a harmonised approach (as the framework above), and by comparing developments within countries with different regulation levels.[9)] One can also assess changes in productivity following a particular change in regulation within a country (for example, the deregulation of an industry, as in Olley and Pakes, 1996) and compare the effects on productivity for other determinants conditional on the regulatory environment. If one observes a regulation change (or some other shock), one can determine whether firms with particular characteristics reacted differently from other firms (a so-called difference-in-difference approach, see Andrews and Cingano, 2012, for an application).

The effect of competition on productivity of incumbents has typically been analysed by simply 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. (2010b), all of which may have their advantages and disadvantages in different contexts. One can also interact the competition variable with other variables to see if the effects of other variables differ with the strength of competition, as in Van Der Wiel et al. (2008) who investigated the speed of convergence to the global and national productivity frontier, depending on the degree of competition. Finally, given the endogenous nature of competition, researchers sometimes rely on changes in regulations as instruments for changes in the competition.

As with competition, a simple way to test for the presence of spillovers, is to add a measure for these spillovers in the production function, which as in the case of innovation can again be thought to parameterise the productivity term A. Naturally, it is a lot harder to actually measure spillovers. Learning from best-practice is usually captured by a so-called distance-to-frontier (DTF), which measures the difference between a firm's productivity and the front-runner's productivity. Spillovers from R&D can be captured by including the aggregate R&D investments of other firms in the same market. Similarly, network effects from ICT are sometimes captured as the (aggregate) usage or adoption of a particular type of ICT by other firms. Typically, the spillover measure takes into account the strength of linkages between industries by using a weighting based on the input-output relations or the mutual transitions of workers (Cincera, 2005; Mun and Nadiri, 2002). While such analyses can produce results that are indicative for spillovers and positive externalities, the questions of the nature of knowledge diffusion and how learning by firms actually takes place are not addressed.

9) Coordinated international efforts to generate multi-country databases based on aggregation of the firm-level data include ESSLimit/ESSLait (Eurostat, see Bartelsman et al., 2014), CompNet (European Central Bank, see Lopez-Garcia and Di Mauro, 2015), and the DynEmp/Multiprod projects (OECD, see Criscuolo et al., 2014).

Dynamics

Introducing changes over time into the framework allows to study the dynamics of productivity. 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

$$\Delta P_t = \sum_j \Delta P_{jt} S_{jt} + \sum_j P_{j,t-1} \Delta S_{jt} \tag{14}$$

where the first part of the decomposition measures the contribution of changes in the industries' levels of productivity ('intra-effect'), and the second part relates to changes in the relative size of industries ('shift effect'). Productivity can be defined as labour productivity as well as TFP. The share can be defined in a variety of ways, but output or employment are used most commonly. Many refinements can be made to this decomposition that enhance the interpretation. The purpose is to show the basic principle, and how it fits the productivity framework. It is possible to distinguish industries into ICT producing, ICT intensive, and non-ICT intensive industries. Note that the productivity difference in (14) is a nominal change, but to analyse relative productivity changes it is possible to take logs and proceed in the same way.

Decomposing industry growth into firm-level changes introduces entry and exit in the equation. If P_j denotes industry productivity, and s_i the relative size of firm *i* in industry *j*, then a general decomposition into the contribution of continuing firms, and entry and exit, is

$$\Delta P_j = \sum_{i \in N} s_{it} P_{it} + \sum_{i \in C} s_{it} P_{it} - \sum_{i \in C} s_{i,t-1} P_{i,t-1} - \sum_{i \in X} s_{i,t-1} P_{i,t-1} \tag{15}$$

where *N*, *C*, and *X* are respectively the population of entrants, continuing and exiting firms in year *t*. Again there are many refinements possible. Various ways have been proposed to further decompose the contribution of continuing firms, which depends on an intra-firm and a shift-effect analogous to the industry case above. Moreover, for entering and exiting firms one cannot calculate growth figures. So how to benchmark the contribution of these firms? Several solutions have been proposed. Balk (2014) provided an extensive overview of possible decompositions.
The observed dynamics may depend on additional variables. For example, competition by nature is also the force that drives the business dynamics, thereby contributing to aggregate productivity. To investigate the role of competition in the process of entry, exit and allocation, 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.

1.4 Industry-level study on the impact of ICT and intangibles

The aim of this section is to provide an illustration of the production function framework using industry-level data. To be able to shed light on the role of various types of capital, we distinguished between IT and non-IT (tangible) capital, and also include intangible capital.

Moreover, we tested whether the effect of intangibles is moderated by the ICT intensity of an industry. Our approach followed the recent work by Corrado et al. (2014) and Chen et al. (2014).

Data

We first described the data sources and the corrections to existing variables required as a consequence of capitalizing intangibles. The data on production, labour, and capital services were sourced from the Dutch Growth Accounts. For the breakdown of capital services in IT and non-IT capital, we made use of existing series on computers and software, and a newly developed series on telecommunication equipment (see chapter 3). We also used data on the services from intangible capital from the Knowledge module (see Van Rooijen-Horsten et al., 2008), as well as the corresponding investments for correcting value added. We treated software and databases as an instance of IT capital, not as an intangible, following Goodridge et al. (2013). Limitations on the availability of the knowledge and IT variables imply that the time-series available for analysis covered 1995 to 2008. All series are for 33 industries in the 'commercial sector', which is the part of the economy for which Statistics Netherlands measures productivity changes. All monetary variables were measured in real terms (i.e. nominal figures deflated using industry price deflators).

Adjustment for intangibles

As described by CHS and Van Rooijen-Horsten et al. (2008), capitalising expenditures on intangibles requires adjustment of both output and inputs. In the traditional National Accounts framework, expenditures on intangibles are either expensed (i.e. they are seen as intermediate inputs), or not accounted for (when produced under own account). With purchased intangibles, intermediate inputs decrease with the size of the investment once they are capitalized. When they are produced in own account, gross output increases with the production value (which equals the investment). Value added (gross output minus intermediate inputs) will always increase with the size of the investment, either through higher gross output or lower intermediate inputs. Denoting the investment in intangibles by *N*, we can therefore make the following correction to value added to account for intangibles

$$VA_{jt} = \widetilde{VA_{jt}} + N_{jt} \tag{16}$$

where the tilde denotes unadjusted value added. Note that *N* is the total investment in intangibles, i.e. aggregated over types and both own-account and purchased. This correction was made in current and constant prices (i.e. in prices of the previous year); this allowed us to calculate the real growth rate of corrected value added. Also *N* excludes those intangibles that were already capitalised in the national accounts and therefore already included in value added: mineral exploration, originals and software.[10] We did correct the capital services series for this, taking out the capitalised intangibles and taking them them together with the new intangibles.

10) During the period in which the project was carried out, the national accounts was revised according the SNA 2008 guidelines, where among other things R&D is now capitalised. We have used data from before the revision.

Specification

We considered the estimation of the following productivity growth equations:[11)]

$$\Delta \ln VA_{jt}/L_{jt} = \theta^{KNIT} \Delta \ln K_{jt} + \theta^{KIT} \Delta \ln KIT_{jt} + (\theta^{L} - 1) \Delta \ln L_{jt} + \theta^{R} \Delta \ln R_{jt} + \mu_{jt} \quad (17)$$

$$\Delta \ln TFP_{jt} = d^{KNIT} \Delta \ln K_{jt} + d^{KIT} \Delta \ln KIT_{jt} + d^{L} \Delta \ln L_{jt} + d^{R} \Delta \ln R_{jt} + \mu_{jt} \quad (18)$$

where as before *VA* and *L* denote value added and labour cost, and *KNIT* is non-ICT capital services, *KIT* is ICT capital services, and *R* denotes intangible capital services. We also estimated a version of these equations without intangibles, hence using unadjusted value added. The main difference between the two specifications is that the former implicitly assumes the elasticities to be the same over all industries (and over time). With the theoretical link to cost shares in mind, this may be a restrictive assumption, given differences in the structure of production over industries. An alternative is to calculate TFP growth via the index approach, and regress on the same explanatory variables, where the coefficients should now be interpreted as deviations from the cost share (Goodridge et al. 2013). So instead of equal elasticities, deviations from the cost shares are assumed to be constant. We used an index based on the Cobb-Douglas function and cost shares in the current year. Table 1.4.1 provides some descriptive statistics for the cost shares in the models with and without intangibles. We also investigated whether the impact of intangibles could be moderated by ICT by making the coefficient on intangibles dependent on the ICT intensity of the industry, that is

$$\Delta \ln VA_{jt}/L_{jt} = \theta^{KNIT} \Delta \ln K_{jt} + \theta^{KIT} \Delta \ln KIT_{jt} + (\theta^{L} - 1) \Delta \ln L_{jt} + (\theta^{R} + \delta D_{j}) \Delta \ln R_{jt} + \gamma D_{j} + \mu_{jt} \quad (19)$$

where *D* is a binary variable indicating that the industry is ICT intensive or not, which is measured by whether the industry median of the user cost of ICT over labour cost is above or below the overall median. A similar interaction was added to the TFP specification.

1.4.1. Descriptive statistics for cost shares, with and without intangibles

	non-ICT capital	ICT capital	labour	intangibles
mean	0.26	0.03	0.71	
min	0.02	0.00	0.03	
max	0.96	0.14	0.96	
mean	0.23	0.03	0.63	0.12
min	0.02	0.00	0.03	0.02
max	0.92	0.12	0.90	0.40

11) Test results strongly suggest that the labour productivity variable has a unit root, which makes it preferable to look at growth rates. Moreover, for TFP it is more natural to look at the growth rates rather than the level.

Results

After a first estimation using the Least Squares Dummy Variable (LSDV) estimator, we detected some outliers, which we excluded from the subsequent analysis.[12] We found no evidence for serial correlation in the residuals, and hence it is not necessary to consider a dynamic specification. Our test results also suggest that the exogeneity of our explanatory variables cannot be rejected. Hence, the LSDV estimator should give unbiased results.[13] Table 1.4.2 gives the results for the four specifications. In the value added specification, we found returns to non-IT capital that are slightly below the average cost share. The labour elasticity implies slightly above normal returns in both specifications. Intangibles provide returns comparable or slightly above the average cost share. Surprisingly, the estimates of the elasticities of ICT capital are small and insignificant in both specifications. Relaxing the assumption of equal elasticities, we found that ICT capital does not have an above normal return. Without accounting for intangibles, this is the case for all inputs. When intangibles are included, however, the results suggest substantial below normal returns for non-IT capital, mirrored by substantial above normal returns of intangibles. These results are roughly in line with the results in Corrado et al. (2014), for various estimation techniques and specifications.

1.4.2. Estimation results productivity equations

	(1)	(2)	(3)	(4)
non-ICT capital	0.209[1]	0.192[2]	−0.0957	−0.201[1]
	(−0.009)	(−0.016)	(−0.171)	(−0.006)
ICT capital	0.004	0.001	−0.009	−0.009
	(−0.958)	(−0.985)	(−0.854)	(−0.848)
labour cost	−0.258[1]	−0.297[1]	0.005	0.016
	(−0.003)	(0.000)	(−0.952)	(−0.887)
intangibles		0.132[2]		0.142[3]
		(−0.044)		(−0.090)

Source: Statistics Netherlands.
All equation include time and industry dummies.
Estimation is by OLS.
Number of observations is 417.
Dependent variable is (log-differenced) value added over labour cost (column 1 and 2), or log TFP (column 3 and 4).
All variables are in log-differences.
[1] Significant at 1%.
[2] Significant at 5%.
[3] Significant at 10%.

[12] We excluded the oil industry in 1997 and 2000, electronics from 2000 to 2002, telecom in 2002, and machinery in 2000.

[13] We estimated the different specifications with GMM using lagged and twice-lagged levels of the explanatory variables as instruments. The instruments were found to be valid (Sargan test), while a so-called *C* test suggests that exogeneity cannot not be rejected. In the labour productivity equation including intangibles, exogeneity can be rejected only marginally, but not in the TFP equations, nor the specification without intangibles. Given the substantial loss of efficiency in the precision of the estimations, we prefer to use OLS controlling for fixed effects. The fact that we can regard the inputs as exogenous may be because we use industry data. Theory suggests that inputs are endogenous because a firm decides on their level with knowledge about its productivity that a researcher does not have. At the industry level, however, the analogue may not completely hold, since the industry does not ‘decide’ on factor levels, and does not ‘observe’ anything.

Table 1.4.3 presents the results of when we interacted the intangibles with the ICT intensity dummy. The interaction term is insignificant, hence we found no evidence that the impact of intangibles differs between ICT intensive and non-ICT intensive industries. The coefficient on intangibles is of a similar magnitude as before, but it drops slightly below the common levels of significance. These results are at odds with those in Chen et al. (2014), who find strong support for positive effects of ICT, both directly and indirectly via its interaction with intangibles. However, as they consider a cross-country industry panel, the identification of the impact could be driven by the country dimension.

1.4.3. Estimation results productivity equations with interaction between ICT and intangibles

	(1)	(2)
non-ICT capital	0.192[2]	−0.201[1]
	(−0.016)	(−0.006)
ICT capital	0.001	−0.009
	(−0.986)	(−0.853)
labour cost	−0.297[1]	0.015
	(0.000)	(−0.891)
intangibles	0.134	0.131
	(−0.137)	(−0.197)
ICT intensity dummy x intangibles	−0.002	0.0165
	(−0.982)	(−0.882)
ICT intensity dummy	0.0144	0.006
	(−0.525)	(−0.777)

Source: Statistics Netherlands.
All equation include time and industry dummies.
Estimation is by OLS.
Number of observations is 417.
Dependent variable is (log) value added over labour cost (column 1), or log TFP (column 2).
All variables are in log-differences, except the ICT dummy.
1) Significant at 1%.
2) Significant at 5%.
3) Significant at 10%.

In sum, overall these results suggest that intangibles are a key determinant of productivity differences, while the role of ICT is limited in the direct impact on productivity and interaction with intangibles. However, while considering capital as a heterogeneous input by distinguishing ICT, non-ICT and intangibles, our model could be further refined. For example, ICT can be broken down into hardware and software. Hardware prices have dropped far more than software prices, hence possibly yielding larger productivity effects. Moreover, the distinction between R&D and non-R&D intangibles could be useful because of possibly different productivity effects and interaction with ICT. So while our results are indicative, it may be too early to conclude that ICT is irrelevant. Moreover these results concern the aggregate level, and say nothing about whether ICT can explain firm productivity growth or productivity differences between firms. The deviations from cost shares could have multiple causes, such as imperfect competition, returns to scale, adjustment costs, spillover effects et cetera. Further research into the most important drivers of these results would therefore be valuable.

1.5 Summary and introduction to the other chapters

In this introductory chapter, we reviewed determinants of economic growth and productivity found in the literature, distinguishing three categories: within-firm determinants, external factors, and the dynamic process that determines how developments at lower levels of aggregation translate into changes at higher levels. We discussed the main determinants in each of these categories, and the role of ICT. We presented a general framework for analysis based on the use of a production function. An illustration with industry data shows that intangible capital is a key determinant of productivity, but the role of ICT seems limited at this level of aggregation and for the period studied.

Now that the stage is set, we will delve deeper into selected topics. Chapters 2 to 4 look at the determinants inside the firm. Chapter 2 focuses on labour and uses information on the price of labour to measure labour quality changes. The contribution of labour to growth is then determined, controlling for changes in the composition of employment. Chapters 3 and 4 focus on the heterogeneity in types of capital goods, specifically ICT. Chapter 3 takes an industry perspective, breaking down ICT capital into hardware, software and communication equipment, and determining the relative contributions to growth, while chapter 4 estimates the productivity effects of various kinds of ICT at the firm level.

The remaining chapters focus on factors that are external to the firm. Chapter 5 looks at the relation between ICT and competition, investigating whether the introduction of online selling has impacted profit margins and, vice versa, whether increasing competition leads to the adoption of online activities. Chapter 6 combines firm-level productivity data with information on the entry and exit of firms, and looks whether differences in the dynamics and distribution of productivity are related to the ICT intensity of the industry. Finally, chapter 7 explores the subject of national and global value chains, and relates the engagement in and intensity of such value chains to ICT usage.

2.

Productivity and labour compostion

The price index of labour corrects the year-on-year developments of hourly wage costs of employees for population changes. The price index and the concomitant composition effects can be used for productivity calculations in the Dutch growth accounts. The average composition effect in the labour volume was 0.5 percentage points per year for the period 2002-2011. When calculated as a residual, multi-factor productivity (MFP) growth falls from 1.2 to 0.7 percentage points per year.

2.1 Introduction

Recent research based on data from Statistics Netherlands has resulted in the price index of labour (Van den Berg and Peltzer, 2012). In contrast to the changes in hourly wage costs, the price index corrects for the changes in labour composition according to background characteristics of employees. We call the difference between the two the composition effect.[1)]

Statistics Netherlands produces the annual growth accounts for productivity analyses (e.g. Van den Bergen et al. 2008). Based on national accounts data, the output – value added and gross production – is linked to inputs – labour, capital and intermediate consumption. Composition of labour was not part of the labour inputs, except for distinguishing between employees and the self-employed. The composition of labour is especially important when studying labour quality. Quality here means traits that refer to the experience, knowledge or skill of an employee. For example, a rise in the level of education is now included in the price of labour rather than the volume of labour. Consequently this underestimation of the contribution of labour to output results in an overestimation of MFP.

This chapter describes the use of the price index of labour for a new time series of labour volumes corrected for changes in composition. We also describe the new MFP estimates when we use these new time series in the growth accounts.

2.2 Labour composition[2)]

Background and method

The yearly change of hourly wage costs can be broken down into price effect and composition effect. The latter is the part of the total change in wage costs that can be attributed to changes in the composition of the population of employees. E.g. older

1) It may also be called a structure effect, but we have chosen to follow international practice and call it composition effect. Also, structure effect, in the context of productivity studies, can refer to production structure, which is something we want to avoid.

2) This section draws heavily upon Van den Berg and Peltzer (2012).

workers usually get paid more than younger ones and the more highly educated more than the less well educated. These changes contribute to the total change of hourly wage costs. To determine the price change of labour, the hours worked are split up according to five characteristics: age, level of education, sex, collective labour agreement (yes or no) and industry[3]. Two of those characteristics can be put together under labour quality, i.e. education and age (as a proxy for experience) whilst the others bring out finer details of the population to ensure a better price index estimation[4].

Monthly wage data from the UWV, the Dutch labour exchange, have formed the basis for the price index of labour since 2006. This source encompasses all wage returns of all employees in the Netherlands, provided by their employers. Before 2006 the Sociaal Statistisch Bestand (SSB)[5] of Statistics Netherlands was used. The UWV and SSB files are enriched with data on education and pension contributions. Age is divided into six classes: <25, 25–34, 35–44, 45–54, 55–64 and 65 and older. Three education classes are distinguished: lower, middle and higher education and 64 industries are distinguished. This results in a total number of 4,608 cells annually. To calculate the composition effect, first the changes in hourly wage cost for each cell are determined. We call these changes the price change:

$$P_{it} = \frac{L_{it}/U_{it}}{L_{it-1}/U_{it-1}} \tag{1}$$

Where P stands for price change, L for wage costs, U the number of hours worked, t the year and i the group of employees in a single cell, based on their background characteristics. All price changes are aggregated into a single (Laspeyres) price index of labour ($\widetilde{P_t}$), by weighing with the share of total wage costs in the previous year (t-1):

$$\widetilde{P_t} = \sum_i W_{it} \cdot P_{it} \tag{2}$$

The weight W is defined as:

$$W_{it} = \frac{L_{it-1}}{\sum_i L_{it-1}} \tag{3}$$

To sum up, the price index of labour is the aggregate of all price changes determined in equation 1.

In a final step, the composition effect (C) can be calculated by dividing the total hourly wage cost by the price index of labour.

$$C_t = \frac{\dfrac{L_t/U_t}{L_{t-1}/U_{t-1}}}{\widetilde{P_t}} \tag{4}$$

[3] The characteristics age, education, sex and are generally included in the literature, see e.g. O'Mahony and Timmer (2009). The inclusion of collective labour agreements as a characteristic is based on their different patterns of (changes in) wage costs.

[4] Even more characteristics can be identified in the composition or price effects, e.g. profession, or part-time / full-time workers. Including more characteristics however hampers the calculation of the price or composition effect because of cells becoming too fine grained.

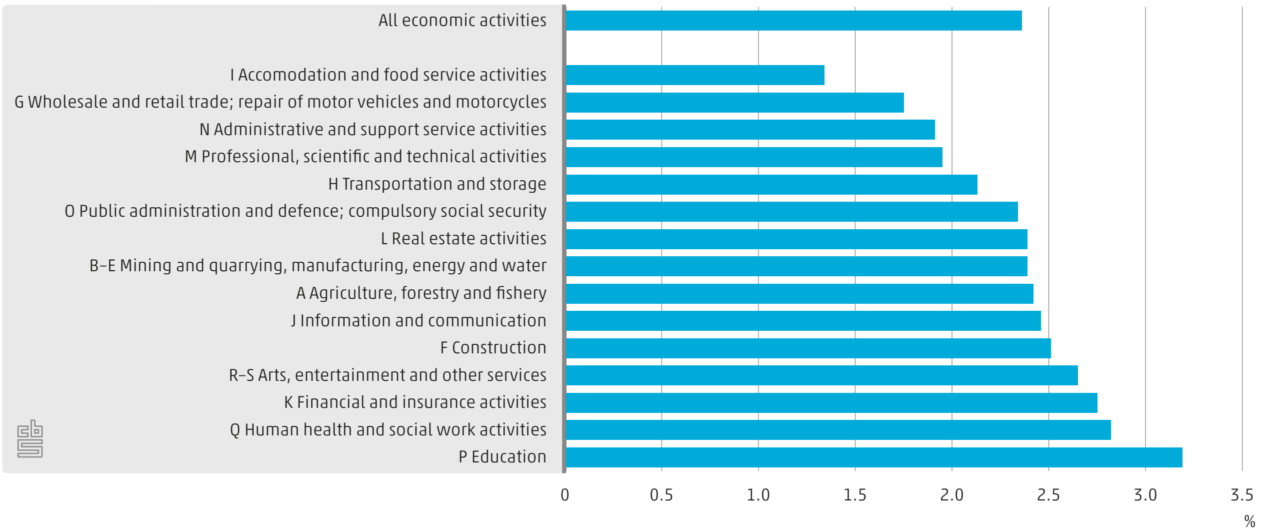
[5] Social statistical file

Conceptually, composition effects are included in the changes in hourly wage costs whereas they are taken out of the price index of labour. The difference between those two can be attributed to changes in the composition of the population of employees. If there were no changes in the composition, then both statistics would be the same and there would be no composition effect (C=1).

Price index of labour

Statistics Netherlands publishes new figures on the price index of labour each quarter. Shown in figure 2.2.1 are the average changes over the years 2002–2011 for the total Dutch economy and for separate industries. Most striking is the large increase in the education sector and the small increase in accommodation and food services. So hours worked in the education sector have become over 3 percent more expensive, independent from any changes in the population of employees in the education sector.

2.2.1 Changes in the price of labour, 2002/2011



2.3 Productivity analysis at Statistics Netherlands

Dutch growth accounts

Productivity is defined as the amount of generated output per unit of input. If the amount of output grows faster than the amount of input, there are productivity gains, and if the reverse is the case, productivity losses.

The output and input of the production process for 33 industries are gathered for the Dutch growth accounts. Both value added and gross production are available for each industry. Dependent on the chosen output, the input measures are labour and capital for value added and labour, capital and intermediate consumption for gross production. On the one hand, for both measures of output, MFP growth is shown as a residual by first subtracting all weighted input growths. Weighting is done by taking the share of each input in total costs. On the other hand, MFP growth can be calculated by dividing the output growth by the combined growth of inputs.

Labour productivity compares one input to output, in our case the hours worked. We divide output by the hours worked to calculate labour productivity. Ideally we move further by separating labour productivity into three components: capital deepening, composition effects and MFP. Each of these three elements of labour productivity contributes to production through its own mechanism. Labour can become more productive by the use of more capital (e.g. machinery) per hour worked. Also, labour productivity can increase by the use of better educated workers, which is reflected in the composition effect. Finally more production can be realised through more efficient use of inputs or technological progress. This last phenomenon is expressed as MFP.

The Dutch growth accounts are fully consistent with the national accounts. However, for some industries no productivity calculations are published because the volume change of inputs is used to determine output[6)]. The use of input-based output prohibits any useful productivity analysis. We call the sum of industries for which independent output measures are available the commercial sector.

Using the price index of labour in the growth accounts

Starting with the contribution of labour to output, we first need to establish the volume change of labour. We first take the change of hours worked for each industry or the commercial sector as a whole. Next, we have to include the composition of those hours worked.

The explicit goal of the price index of labour is to measure price changes of labour as precisely as possible. This means that changes in the population of workers should not influence the price. The opposite applies to the labour volume. Changes in the population should be reflected in the volume changes of labour. For instance, any increase in more highly educated people with their higher wages, should be included in the volume instead of the price, because this change implies a quality improvement. Using the price index of labour fulfils this condition. Or put otherwise, combining the composition effect with hours worked gives the correct volume measure of labour.

$$V_{jt} = {}^{U_{jt}}\!/_{U_{jt-1}} \cdot C_{jt} \qquad (5)$$

Where V denotes the volume change of labour, U the hours worked and C the composition effect of industry j in year t.

Different calculations have to be made to measure the labour income of self-employed people. Hours worked are available from the labour accounts, but these do not provide any data on their remuneration. To mend this gap, we took the annual wage for an employee in the same industry - except for the self-employed in construction for who we impute the

6) These industries are public administration, public services and compulsory social security, education, real estate activities and rental and leasing activities.

same hourly wage as employees. Another exception are the self-employed in health care. For this group we imputed a standardised income, because their background characteristics differ strongly from employees in health care (Van den Bergen et al. 2008).

As an alternative to equation 5, the volume change of labour can be calculated by deflating wages and labour income of the self-employed (L) with the price index of labour (P), i.e. we divide all labour costs by the price.

$$V_{jt} = \frac{L_{jt}/L_{jt-1}}{P_{jt}} \qquad (6)$$

Both equations provide the same labour volume (V)[7].

Employees and the self employed

The price index of labour and its concomitant composition effect applies only to employees. The self-employed in the context of national accounts have no directly observable labour income. Furthermore, background characteristics are often lacking. As a result there is no composition effect available for the self-employed.

In growth accounts the labour inputs of employees and the self-employed together form the total labour input. When applying the composition effect for employees, the self-employed should also receive a composition effect. We have assumed that the composition effect of the self-employed is the same as that of employees. This is a somewhat rough assumption, but given the low share of self-employed people in most industries, it does not affect the outcomes much. One exception is agriculture. Here most labour is done by self-employed people and using the composition effect of employees here is not warranted. Therefore agriculture is not shown separately in the results.

Using a short time series for which both background characteristics of employees and self-employed people were available, we gauged the difference between the two groups. Analyses show that the composition effect of employees in agriculture is different from that of the two groups combined. For the single years, the difference varied between 0.1 and 1.1 percentage points[8]. In comparison, the maximum difference for other industries was 0.4 percentage points for a single year.

The upper lines of table 2.3.1 show the magnitude of excluding agriculture in the total of the commercial sector. Rounded off it amounts to zero for the period 2002-2005. Only in one single year did it exceed 0.0. The small differences stem from the relatively small share of agriculture in the commercial sector. Presenting labour volume changes on the commercial sector as a whole, including agriculture, is therefore warranted and so we show the commercial sector including agriculture in the table.

7) The equivalence can be shown by replacing C in equation 5 by the expression in equation 4 and then rearranging.
8) For this brief time series only age, education and sex were available as background characteristics.

2.3.1 Composition effects of the commercial sector and agriculture, employees and the self-employed, 2002/2005

Industry	Employees/Self-employed	Composition effect
		%
Commercial sector	Employees and self-employed	0.9
Commercial sector without agriculture, forestry and fishing	Employees and self-employed	0.9
Agriculture, forestry and fishing	Employees and self-employed	0.3
Agriculture, forestry and fishing	Employees	0.5

Source: Statistics Netherlands.

2.4 Results

On average the annual contribution of the composition effect to labour productivity is 0.5 percentage points for the commercial sector. This is a sizeable contribution over the period 2002–2011. It even surpasses the contribution of capital. Note here that the figures in table 2.4.1 refer to contributions to output, where the volume changes have been weighted by the share in total costs of inputs.
Zooming in on different industries we see that no industry shows a negative contribution to output for the composition effect.[9] The largest composition effect is in the financial

2.4.1 Growth accounts based on value added, labour productivity, 2002/2011

			Labour productivity			
				of which		
	Value added	Hours[1]		capital deepening	composition effect[1]	productivity, MFP
	%-volume change	%-change		%- point change		
Commercial sector (incl. agriculture), of which	1.6	0.1	1.4	0.2	0.5	0.7
A Agriculture, forestry and fishing	.	.	.	.	.	.
B-E Mining and quarrying, manufacturing, energy and water	1.1	–1.5	2.7	0.8	0.5	1.4
F Construction	–0.8	–0.7	–0.1	0.3	0.7	–1.1
I Trade, transportation, accomodation and food	1.8	–0.1	2.0	0.4	0.7	0.9
J Information and communication	2.2	–0.5	2.7	0.4	0.7	1.6
K Financial and insurance activities	3.3	–1.0	4.3	–0.1	0.9	3.5
M-N Business activities excl. rental and leasing	0.4	1.0	–0.7	0.2	0.7	–1.5
Q Human health and social work activities	3.5	3.0	0.5	0.1	0.3	0.2
R-S Arts, entertainment and other services	0.0	1.5	–1.4	0.2	0.0	–1.7

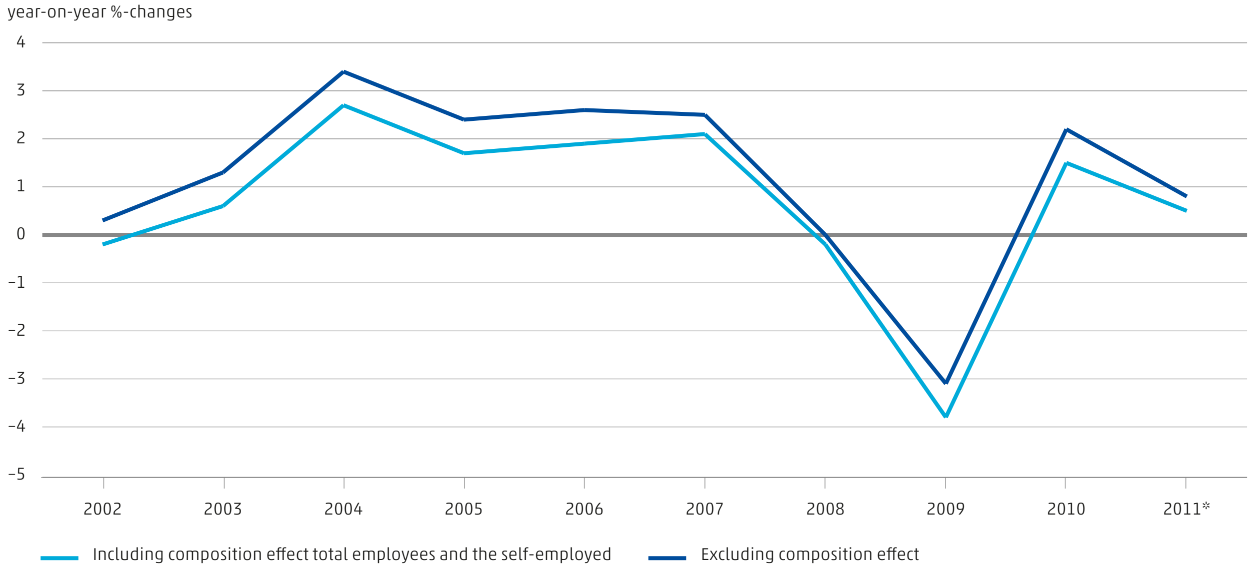
Source: Statistics Netherlands.
[1] Total of employees and self-employed.

[9] The grouping of industries is slightly different from that presented in figure 2.2.1. Growth accounts usually present the industries mining and quarrying, manufacturing and supply of water and energy separately. Health care, on the other hand, is part of a larger group which also comprises public administration and education. Since it is the only industry in this group for which we can derive any meaningful growth accounts we have shown it separately.

and insurance activities and it is smallest in arts, entertainment and other services. Some industries do show negative MFP. These negative changes can occur because firms use their resources inefficiently or because of new investments which will only become profitable after a while.

Productivity growth for the commercial sector is 0.7 percent. The composition effect of 0.5 percent used to be included in productivity growth, meaning that MFP was estimated at 1.2 percent. So the composition effect explains 44 percent of productivity growth in the period 2002-2011 as estimated previously in the growth accounts.

2.4.2 Productivity changes in the commercial sector, incl. agriculture



The published MFP estimates were higher than the ones calculated when the composition effects were incorporated. This is quite logical because MFP also explained the year-on-year changes in the composition of labour. For instance, when there is a positive composition effect as a result of better educated or more experienced workers, MFP is overestimated when the old methodology is used.

2.5 Conclusion

A change in the hourly wage cost can occur because of labour price changes or changes in the composition of the population of employees. The price index of labour explicitly takes these effects into account by distinguishing five background characteristics of employees.

A correct measure of the labour volume is essential for productivity analyses. Up until now the changes in labour volume were based on hours worked. Apart from the hours worked, the composition effect is an integral part of labour volume. The contribution of the composition effect to labour productivity change amounted to 0.5 percentage points for the period 2002–2011. It is higher than the contributions of hours worked and of capital deepening. The composition effect used to be included in MFP. By quantifying this effect, MFP change goes from 1.2 to 0.7 percent.

All estimates presented in this paper use the assumption that the changes in composition of the population of employees are the same as those among the self-employed. Using this assumption for industries with a large share of self-employed people, e.g. agriculture, is too coarse and can lead to biases in the estimates of labour volume changes. Future research in this field should be directed towards establishing a good measure of the composition effect of the self-employed.

3.

Types of ICT and their contributions to economic growth

Given the variety in types of ICT, we analysed the relative importance of different ICT aspects for economic growth using existing and newly developed time-series, and growth accounting techniques. We found that computers are most important for growth, owing to large price decreases. Software makes the second largest contribution, and has gained in importance. The contribution of communication equipment is small, in line with the size of this category. Furthermore, we investigated alternative deflators, and made comparisons with other countries.

3.1 Introduction

The goal of this chapter is to analyse the relative importance of different types of ICT capital in the Dutch growth accounts. The contributions of capital input, labour input and productivity to the volume change of output are presented in a standard growth accounting framework. Capital input is broken down into ICT capital and non-ICT capital. In turn ICT capital is broken down further into the asset types computers, software and communication equipment. Time-series of investments are used to estimate ICT capital stock and the user cost of ICT capital. In previous publications by Statistics Netherlands, computers and software were already distinguished as separate asset types in the investments and capital stock. However, the individual contributions of these asset types to economic growth have not been shown before in the Dutch growth accounting framework. Furthermore, communication equipment was not yet available separately in the investment time-series and was included in the asset type machinery. Therefore, the contribution of ICT capital including communication equipment to economic growth could not be analysed separately. The current chapter makes this extension.

The asset type 'communication equipment' was separated from the asset type 'machinery' in the investment time-series. As a result the service lives of machinery have been adapted and new capital stock values, time series for the consumption of fixed capital, revaluation and other changes were estimated with the perpetual inventory method for communication equipment and machinery. This enabled us to estimate user cost of capital by ICT asset types and the presentation of the contributions of different ICT asset types in a growth accounting framework.

This chapter presents the method and results of differentiating ICT and non-ICT capital in the Dutch growth accounts. The remainder of this chapter is structured as follows. Section 3.2 describes which ICT asset types are used, how communication equipment was separated from the asset type machinery in the investment time-series, and how the contribution of ICT capital to economic growth was determined. Section 3.3 provides an overview of the results for the commercial sector. Moreover, an interesting sensitivity analysis was performed, using alternative deflators for software and communication equipment. Also we compare the results of the Netherlands to other European countries based on the Total Economy Database/EUKLEMS. Section 3.4 summarises and concludes the chapter.

3.2 Method

ICT investment

This chapter focuses on the contributions of different types of ICT capital to economic growth. ICT investment is defined as total investment in computer hardware, software and communication devices (cf. Stiroh, 2002 and Jorgenson, Ho and Stiroh, 2008). To measure ICT investments we used the internationally agreed asset classifications aligned to ESA 2010 and SNA 2008.

Investments (or in national accounting terms, gross fixed capital formation) consist of 'resident producers' acquisitions less disposals of fixed assets during a given period plus certain additions to the value of non-produced assets realised by the productive activity of producer or institutional units' (ESA 2010). This means that investments can be purchased or produced on own account. With regard to ICT investments, for example, a large part of software investments is produced on the own account of enterprises. Fixed assets are defined as produced assets that are used in production for more than 1 year.

The ESA 2010 classification of assets with a link to ICT distinguishes between Information and Communication Technologies (ICT) equipment (AN.1132) and Computer software and databases (AN.1173).

The category *ICT equipment* is defined as 'devices using electronic controls and the electronic components used in the devices'. For the Netherlands, we make a further distinction within this category between the asset types computers and communication equipment.

Computer software is defined as 'computer programs, program descriptions and supporting materials for both systems and applications software. Included are the initial development and subsequent extensions of software as well as acquisition of copies that are classified as computer software'.

Databases are defined as 'files of data organized to permit resource-effective access and use of the data'. In our case, computer software and databases are combined and further referred to as the asset type software.

Until recently, in the Dutch national accounts investments in communication equipment were included in the asset type machinery and were not published as a separate asset type in the investment time-series. For analytical purposes a specification of investments in communication equipment was sometimes made based on CPA code 32 (classification of products by activity according to NACE rev.1). This product category contains products such as printed circuits, telephones and mobile phones, television cameras, digital cameras, video-recorders, etc.

For the purpose of the ESA 2010 revision of the national accounts we made a new estimate for investment in communication equipment. The new estimation method used the ICT survey with questions on the purchase of communication equipment (telephones, etc.)

and other IT equipment (videos, cameras etc.). For small firms (firms with less than 10 employees) investment in communication equipment was based on a ratio with computer investments sourced from the investment survey. Data from the supply and use tables and investments in CPA code 32 were used to reconstruct an investment time series in current and constant (i.e. previous year's) prices by industry.
The results of this new estimation were used in this project for calculating capital stock and the contributions of communication equipment and other ICT asset types to economic growth.

ICT capital stock

Capital stock is measured with the perpetual inventory method (PIM) which, in a consistent way, provides statistics on the consumption of fixed capital, the net capital stock and the productive capital stock. The outcomes of capital stock measurement provide the necessary statistics for compiling balance sheets and growth accounts. The underlying method for measuring capital stock is described by Van den Bergen et al. (2009) and is fully consistent with the Handbook on Measuring Capital (OECD, 2001).
To estimate capital stock, long time-series of investment are needed. For the asset types computers and software we used the available investment time-series and capital stock data. For communication equipment, new capital stock values had to be estimated based on the newly estimated time-series of investment, starting in 1952.

The consumption of fixed capital is the decline in value of fixed assets owned as a result of normal wear and tear and obsolescence. Consumption of fixed capital in the national accounts is different from the depreciation allowed for tax purposes or the depreciation shown in the business accounts. According to ESA (3.141) consumption of fixed capital is estimated on the basis of the stock of fixed assets and the expected average economic life (or service life) of the different categories of those goods.

Since the average service life of communication equipment is shorter than that of machinery, the latter had to be adapted after separating out the investments in communication equipment, and consequently the capital stock for machinery also had to be recalculated. In the old estimates of the capital stock, the asset type machinery had a maximum service life of 40 years, but after removing communication equipment its service life increased to 43 years.
The service life for communication equipment was set at 5 years, similar to the default service life of computers. Software has an average service life of 3 years (which will be adapted to 4 years after the ESA 2010 revision).

Growth accounts

The contribution of the different types of ICT capital to economic growth are analysed in our growth accounting framework. A detailed description of the Dutch growth accounts methodology is found in Van den Bergen et al. (2008). A short summary is provided below. The Dutch growth accounts describe the determinants of economic growth, with multi-factor productivity (MFP) representing a measure of change in the efficiency of production processes. The multi-factor productivity index is determined by dividing a volume index of the outputs by a volume index combining all inputs.

In this study, we used the value-added based productivity model in order to compare the contributions of inputs to economic growth across industries. In the value-added based productivity model, capital (K) and labour (L) are used as inputs to generate value added (VA) as the output. An alternative model is the gross output-based model, where (K), labour (L), energy (E), materials (M) and services (S) are used as inputs to produce consolidated (gross) output. The latter model results in the so-called KLEMS MFP estimate.

The volume index of total inputs is determined by weighing the volume indices of each input with their shares in total cost. The volume index of labour is based on hours worked by employees and the self-employed. The cost of labour consists of the compensation of employees plus an imputed compensation for labour of the self-employed. Labour quality is not yet integrated in the volume measure of labour input. The results of De Bondt et al. (2014) (see also chapter 2) based on the price index of labour will be implemented in the official productivity figures after the ESA 2010 revision.

The user costs of capital are estimated for fixed assets, inventories, subsoil assets and land. The volume index of the capital services of fixed assets is based on the volume changes of productive capital stock. This capital stock measure is corrected for efficiency losses due to ageing. Capital cost is determined by multiplying the quantity of assets, broken down by asset type and age, with the user cost per quantity of assets. The user cost represents all (imputed) cost to hold and use an asset in production for the period of one year. It contains the following elements: (imputed) interest (or rate of return) representing the opportunity cost of holding the asset, consumption of fixed capital, and holding gains and losses. An exogenous rate of return is used, represented by the interbank interest rate supplemented by a constant risk premium.

The user costs of other types of capital inputs are estimated in a similar way, although slight differences apply for certain types. The volume changes of the capital services derived from subsoil assets are based on physical extraction levels. For inventories, we used the quantity levels of inventories by commodity. Volume changes of the use of land are derived from data on land surface area by type, corrected for quality (spatial) differences.

The Dutch growth accounts systematically quantify the contribution of individual inputs to output growth at industry level. The contribution of one particular input, say labour, to output growth is determined by examining how much output would have changed in the hypothetical situation that only labour input would have changed and all other inputs and MFP had remained constant. So the contribution of labour is determined by multiplying the volume change of labour input with the share of labour in the total production cost. Subsequently, multi-factor productivity growth can be interpreted as that part of output growth that cannot be explained by any growth of inputs. As such, multi-factor productivity change is determined as a residual in the growth accounts and represents a change in the efficiency of existing production processes.

The Dutch growth accounts use the concept of the commercial sector to aggregate industry outcomes to a macro-economic total. The commercial sector covers the entire economy except the industry branches public administration and services; education; renting, buying, selling real estate; renting and leasing of tangible goods; and activities of households. The main reason for excluding these economic activities is the absence of proper indicators for measuring their output volumes.

3.3 Results

Growth contributions of ICT capital

In this section we present the results of specifying different types of ICT capital in the Dutch growth accounts. Overall, the contribution of capital input to real value added growth is slightly lower than the contribution of labour input and the main part of the contribution of capital input is determined by ICT capital.
On average ICT capital explains 65 percent of the contribution of total capital to economic growth over the entire period 1996–2009. Computers are responsible for 43 percentage points, software for 21 percentage points, and communication equipment for only 1 percentage point of the total contribution of capital input.

3.3.1 Contributions to value added volume changes

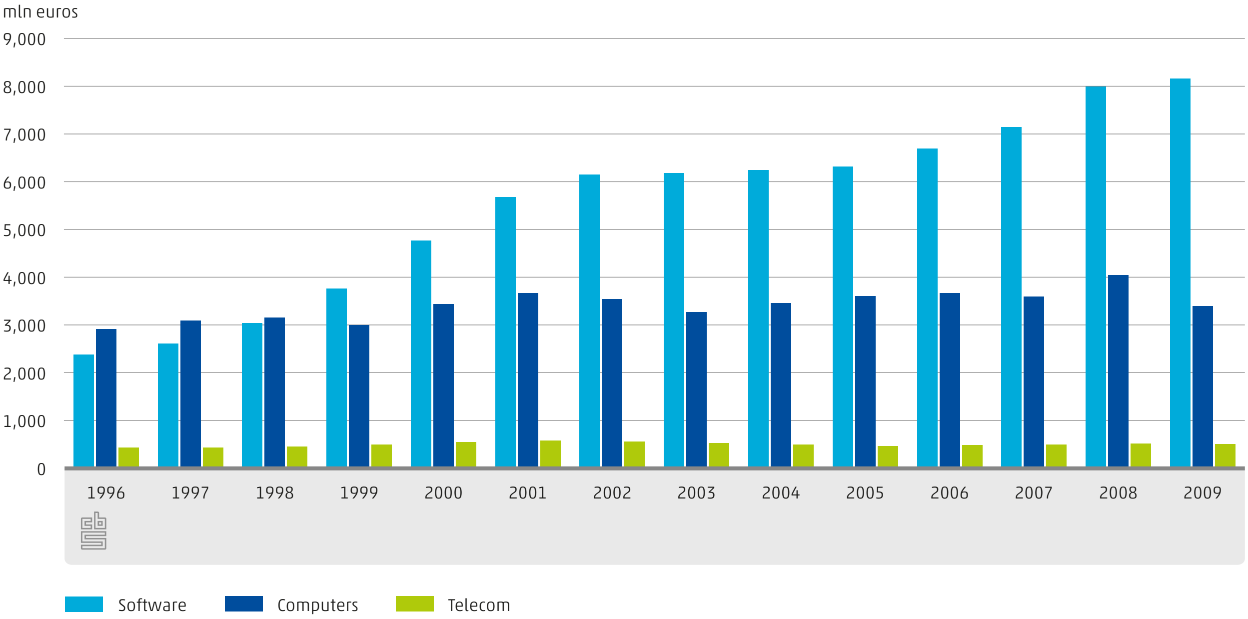
	1996/2001	2002/2008	2007	2008	2009
	Percentage points				
Labour	1.6	0.4	1.9	1.5	–1.2
Capital	1.2	0.3	0.4	0.9	–0.1
ICT capital	0.7	0.2	0.3	0.2	0.2
computers	0.5	0.2	0.2	0.1	0.1
software	0.2	0.1	0.1	0.1	0.1
communication equipment	0.0	0.0	0.0	0.0	0.0
Non-ICT capital	0.5	0.1	0.2	0.6	–0.3
Productivity	1.1	1.8	2.5	0.0	–3.1
	% volume changes				
Value added	4.0	2.4	4.8	2.3	–4.4

Source: Statistics Netherlands.

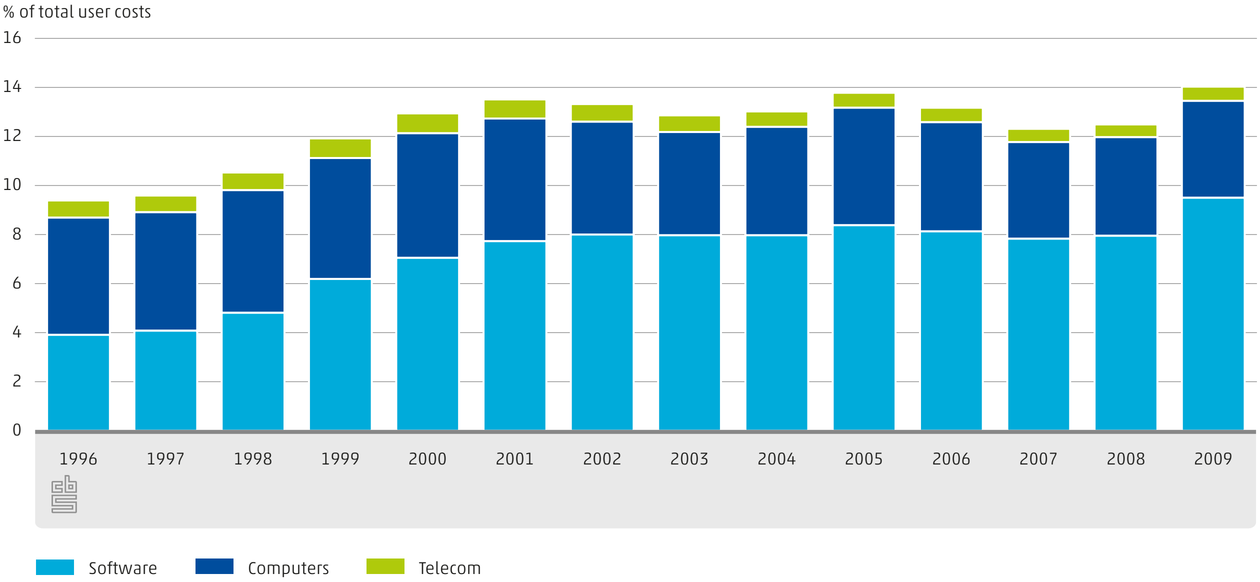
The relative size of the user cost of capital in current prices of the three different types of ICT capital are shown in figure 3.3.2 for the commercial sector. While the user cost of software had an initial value below the user cost of computers, they showed a large increase and reached a level of 2.4 times the user cost of computers in 2009. Even at times when investments in computers fell, the user cost of software continued to rise. There was a brief slow-down of the growth in user cost between 2002 and 2005 due to a slow-down in software investments. The results by industry are available on request.

Figure 3.3.3 shows the shares of ICT capital in the total user cost of capital. This is one of the building blocks for calculating the individual contributions to output growth. ICT capital has a relatively low cost share (12 percent on average) compared to the large contribution ICT capital makes to value added growth (65 percent of the total contribution of capital input). In 2006 and 2007 the input cost share of ICT capital fell, while figure 3.3.2 showed a strong increase of the user cost of software. Apparently, the other types of (non-ICT) capital increased more in value terms during these years, resulting in a lower cost share for ICT capital. Again results by industry are available on request.

3.3.2 User cost of capital of different ICT asset types

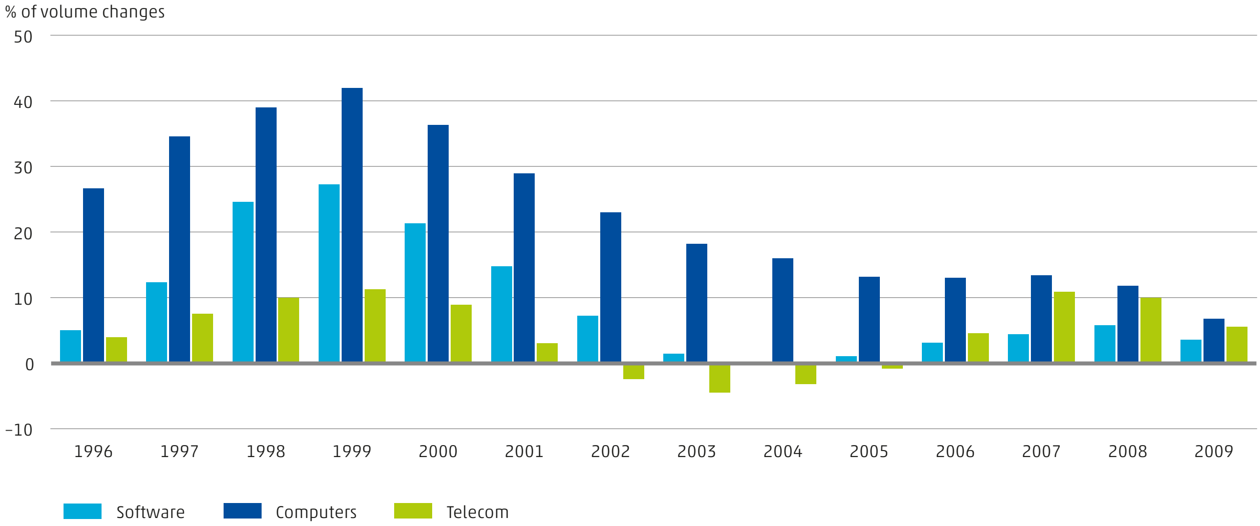


3.3.3 Shares of different types of ICT in total user costs of capital

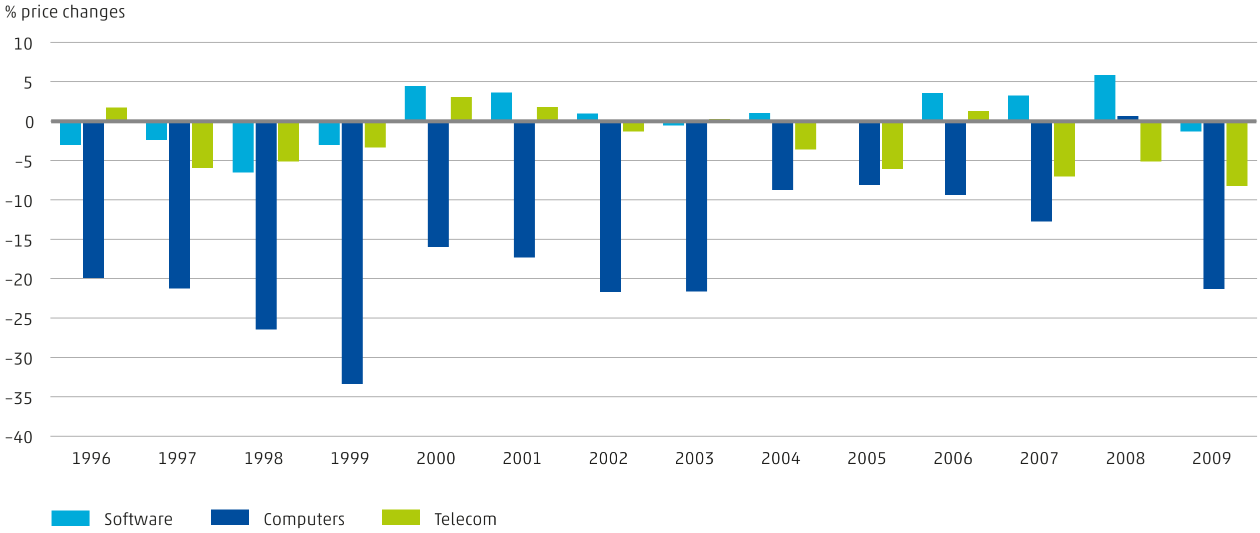


Figures 3.3.4 and 3.3.5 present the volume changes and the price changes of the different types of ICT user cost of capital. Computers show an enormous volume increase. These volume changes are mirrored by a persistent drop in prices, which is caused by the increasing quality of computers for which the computer prices are corrected. The value of a computer remains relatively stable over time, but computing power increases every year. Although computers showed a very large volume increase, their share in total user cost decreased from around 5 percent in the late nineties to 4 percent in 2009. In contrast, the cost share of software increased from around 4 percent in 1996 to almost 10 percent in 2009.

3.3.4 Annual volume changes of different ICT user cost of capital



3.3.5 Annual price changes of ICT user costs of capital



The price developments of the user cost of capital also contain annual fluctuations of the rate of return. Therefore, the annual price changes that are shown are not completely representative for the price developments of the underlying asset types (i.e. the price changes concern the user costs, and not the investment goods). However, the exogenous rate of return in the Dutch growth accounts is not industry and asset type-specific. As a consequence, changes of the rate of return are reflected in all asset types in a similar manner.
The figures show that the prices of software and communication equipment did not decline like the computer prices did. For software this can be explained by the fact that much software is built on own account and that its estimates are based on the cost of producing the software. Communication equipment is a mix of different kinds of products, including products whose quality has greatly improved (such as mobile phones) and far less

improved products such as wired telephones or television cameras. However, in general, the question whether estimated price developments of various types of ICT appropriately control for quality changes is an outstanding issue (Byrne et al., 2013).

Sensitivity to different deflators

In the previous section we showed that the deflators of different types of ICT capital behave differently. Computer prices fell sharply over time while software and communication equipment exhibited far less steep developments. To explore the effects of different prices and to see what happens to the growth contributions if all ICT capital would receive the same deflator of computers, we conducted a sensitivity analysis.

3.3.6 Capital contributions with computer deflators for ICT capital, commercial sector

	Official data	Computer deflator
	Percentage points	
Capital	0.7	1.1
ICT capital	0.4	0.9
computers	0.3	0.3
software	0.1	0.5
communication equipment	0.0	0.0
Non-ICT capital	0.2	0.2

Source: Statistics Netherlands.

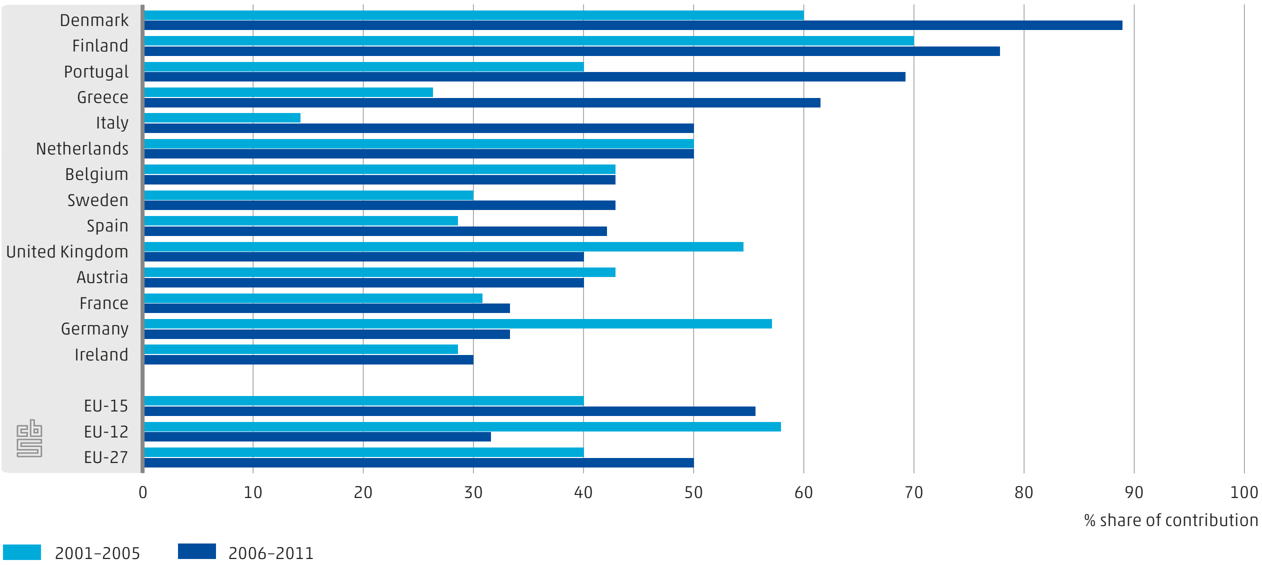
On average, the contribution of ICT capital to output growth would double if computer deflators were used for software and communication equipment. The contribution of software would become almost 4 times larger and of communication equipment over 5 times larger (although still not above 0.0 due to its small cost share). Although computer deflators are an extreme case for the price developments of software and communication equipment, the analysis confirms that growth contributions are sensitive to the price index chosen.

It should be noted that different deflators for software and communication equipment would also influence the volume change of value added (through own-account production). This does not affect the contribution in table 3.3.6, but does affect the contribution of MFP. It could be interesting to analyse these effects in a follow-up study.

Comparison with other countries

To compare the results of the contribution of ICT capital to output growth in the Netherlands with other countries we used van Ark et al. (2013) who provided an updated view of the contribution of ICT and non-ICT capital per hour worked to labour productivity for all EU member states. Based on these growth contributions, we derived the shares of ICT capital in the contribution of total capital to output growth. Results for the 15 and 12 ‘old’ member states and EU aggregates are presented in figure 3.3.7.

3.3.7 Share of ICT capital in the contribution of capital to output growth



Source: Van Ark et al. (2013), The Conference Board, Total Economy Database.

The shares of ICT capital in total capital contribution for the Netherlands average 50 percent, which means that over the period 2001–2011 ICT capital contributed just as much to value added growth as non-ICT capital. The Netherlands has an intermediate position, while Denmark and Finland score relatively high. The position of the Netherlands has remained stable, while the share of ICT capital in the aggregate of the EU-27 member states increased between the two periods.

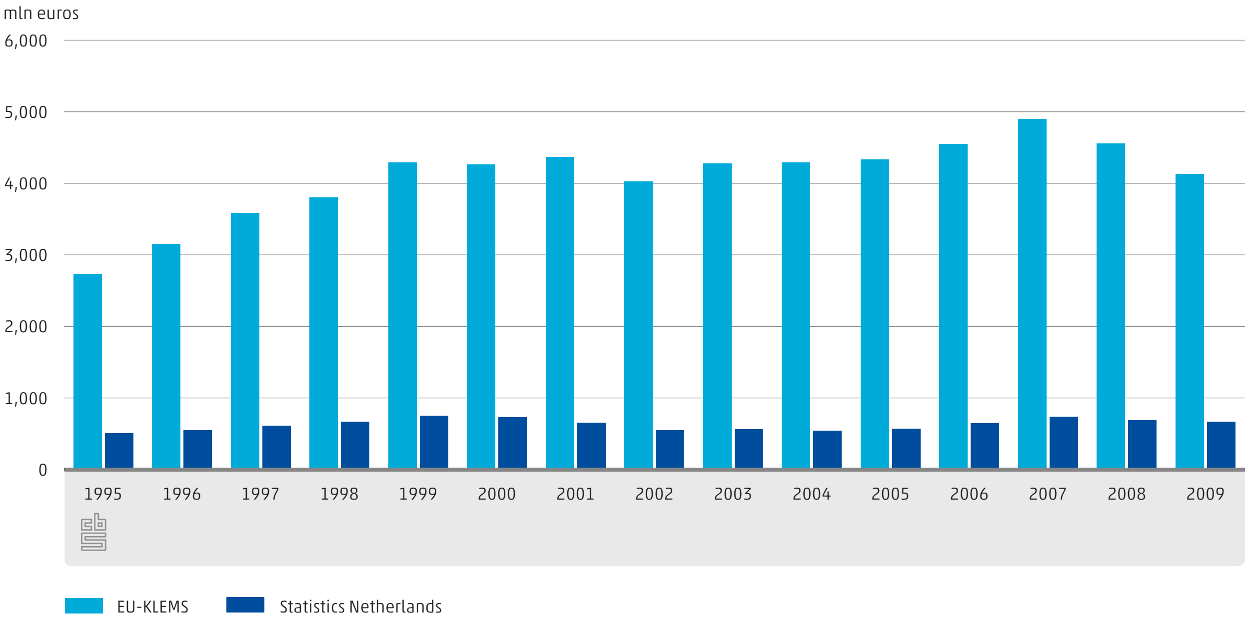
When we compared the results for the Netherlands from the Total Economy Database (based on EUKLEMS) with our own results for the contribution of ICT capital as a share in total capital we found that ICT capital had a larger share in the period 1996–2009, namely 65 percent of the contribution of total capital input. For the period 2001–2005 the share of ICT capital in the contribution of total capital is even larger (78 percent).

An important explanation for these differences is that non-ICT capital in the Dutch growth accounts includes several additional asset types such as land and subsoil assets that are not included as separate asset types in the EUKLEMS and the Total Economy Database. Therefore, the growth contributions of ICT and non-ICT capital cannot be compared directly as volume changes of land and subsoil assets may have a downward effect on the contribution of non-ICT capital, resulting in a larger share for ICT capital.

Since software investments and computer investments in the EUKLEMS database were sourced from Statistics Netherlands, we focused on the differences between our new estimate for communication equipment and EUKLEMS. As official investment statistics on communication equipment for the Netherlands were not readily available, an estimate for this type of ICT capital was implemented in the EUKLEMS database. In addition, in the EUKLEMS definition, all investments made by industry 64 (NACE rev. 1, Post and telecommunications) are counted as investment in ICT. Moreover, for the other industries, the estimates were based on the share of communication equipment in non-structures investment calculated from the average shares by industry for France, Germany, the UK and the USA, on an industry basis (Timmer et al., 2007).

This approach has resulted in an estimate for total investments in communication equipment that is substantially larger than the figures for communication equipment presented in this report (see figure 3.3.7). On average, investments in communication equipment in the EUKLEMS database are 6.5 times larger than our investment figures based on the ESA-asset classification. As a result, the input cost share of communication equipment and the contribution of communication equipment to output growth also became larger than we found here.

3.3.8 Nominal gross fixed capital formation in communication equipment



Source: Statistics Netherlands and EU-KLEMS.

In general, telecommunication networks are often counted as ICT investments, but they are not part of the ESA definition of ICT equipment (AN.1132). For analytical purposes and further harmonization of international data it would be helpful if these different types of ICT investments could be specified in more detail. Also more guidance from international organizations is needed to come to a more harmonised definition and measurement of ICT capital.

3.4 Conclusion

The aim of this study was to specify different types of ICT capital in a growth accounting framework. Extant time-series of investment in software and computers and a newly developed time-series for communication equipment were used to determine the contributions of these asset types to output growth. Communication equipment had to be specified in order to present a breakdown of ICT and non-ICT capital in the Dutch growth accounts. Not surprisingly we found that the growth contribution of communication equipment is very small (invisible), because of the small share in total input cost.

The results showed that ICT capital in the Netherlands is responsible for much of the contribution of total capital to output growth of the commercial sector. The share of ICT capital in total capital contribution has increased from 58 percent in the years before the dot-com crisis to 78 percent in the period 2002–2008. Computers are responsible for (on average) 43 percentage points, software for 21 percentage points, and communication equipment for only 1 percentage point of the total contribution of capital input. Computers owe their large contribution to persistent price decreases, caused by the increasing quality of computers for which the computer prices are corrected. While the user cost of software had an initial value that was below the user cost of computers, they showed a large increase and reached a level of 2.4 times the user cost of computers in 2009. It also appears that ICT capital has a relatively low cost share (12 percent on average) compared to the large contribution ICT capital makes to value added growth (65 percent of the total contribution of capital input).

It was further shown that the Netherlands has an intermediate position between EU-15 member states with respect to the use of ICT capital in relation to non-ICT capital. Differences between EUKLEMS and results from Statistics Netherlands can be explained by a different coverage of asset types (land, subsoil assets, etc.), a different growth accounting method (exogenous vs. endogenous, quality of labour etc.) and the specification of different asset types.

Constructing these series, we found that the international guidelines are unclear about the inclusion of certain asset types in ICT capital. For example, it is not clear whether investments in communication networks should be included. The infrastructure for communication networks is part of the asset category other structures (AN.1122) and does not fall in the ESA asset categories of ICT equipment and software and databases. Investments in IT infrastructure are clearly necessary conditions for ICT use. Although the user cost of infrastructure in the information and communication industry are relatively small (about twice the user cost of communication equipment) and including them in the growth accounts would not change the overall picture very much, the issue needs further discussion. Moreover, expenses on radio spectra (AN.2151) such as 4G could be included as well, as they represent a large part of the cost for telecom providers to produce their services. Currently, expenses on radio spectra are not included in the Dutch non-financial balance sheet, so this could be a topic for further research, before their user cost of capital can be estimated in a growth accounting framework.

The results also showed that growth contributions are sensitive to the deflators used. By way of a thought-experiment, we analysed the sensitivity of the growth contributions to using computer deflators for software and communication equipment. The actual deflators of the latter two asset types showed much less decline than the one for computers. This relates to the fact that quality adjustment has proved to be much harder for software and communication equipment. The experiment resulted in a growth contribution of software and communication equipment that was 4–5 times larger and a contribution of ICT capital that was two times larger. In general, quality improvements are hard to measure, especially when input approaches are used for the measurement of output. Further research into ICT price and volume measures is therefore recommended.

4.

Types of ICT and firm-level productivity

ICT embodies a broad range of assets, including computers, software and communication technology. Its applications, and the corresponding performance effects, can be very diverse. In this chapter we relate the usage of and investment in different types of ICT to firm performance. We found that the association to firm performance differs for each type of ICT and that it matters whether one is interested in productivity or sales per worker.

4.1 Introduction

It is by now well documented in empirical studies at different levels of observation that investment in ICT goods may earn higher returns than other types of capital (e.g. Draca et al., 2006; Kretschmer, 2012). Besides indicating that there may be special features to ICT that help explain productivity differences between firms, industries and countries (e.g. the degree of co-investment in non-accounted complementary intangible assets, or the existence of substantial externalities and network effects), this result underlines the usefulness of distinguishing different types of capital when looking at contributions to productivity, rather than assuming that a single homogeneous capital stock exists.

As noted in Wilson (2009) there are several reasons for taking an interest in the heterogeneous nature of capital. Due to complementarities among different capital goods, the 'capital mix' (i.e. the overall composition of the entire capital stock), it is inappropriate to consider capital as being homogeneous. Moreover, if different types of capital have a different impact on productivity, this should have consequences for investment incentive policies. That is, the right asset types should be targeted, and different types of assets may require different policies.

ICT manifestations come in a large variety, even within this capital subcategory. The first distinction is between hardware and software. For example, Corrado et al. (2006) view computerised information (i.e. databases and – mainly – software) as an instance of knowledge capital (or intangible assets), and as a separate input into the production function. Hardware can be broken down into computers, communication equipment, and network technology, while software can be broken down into different types of software, and purchased packages versus software developed by the firm on its own account. Mainly due to data restrictions, however, not much empirical work exists that makes a distinction between the various types of capital beyond that between ICT and non-ICT capital, especially not at the firm level.

A notable exception is the work by Wilson (2009) who makes use of an extensive survey on the investment in different types of capital by firms. He shows that the implied marginal product of most types of capital are in line with the rental prices, indicating that there are no excess returns to most types of capital. However, for computers, software and communication and some other types of capital the marginal product largely exceeds the rental price. Moreover, the excess returns differ between these subtypes of ICT. Although his results are based on a cross-section, there are some robustness checks that indicate that they are not driven or biased by endogeneity problems.

Some studies have attempted to overcome the lack of appropriate investment or capital stock data with the use of proxies. For example, Atrostic and Nguyen (2007), use the book value of computer capital stocks, and introduce a binary variable for the usage of network technology. They found that in their preferred sample of new firms, computer networks have an additional effect on productivity over and above that of computers only. In a larger cross-country study on the economic impact of ICT, Van Reenen et al. (2010) studied the relation of different forms of ICT to productivity, among many other things. They proxy ICT (hardware) capital with the percentage of workers using a computer, own-account software by the percentage of ICT staff in relation to the total number of employees, and purchased software and network technology by counts of particular technologies related to those types of ICT. Using simple regressions and several sparse specifications, they found that software and network technology have a positive correlation with productivity, even after controlling for ICT capital, except for purchased software. They also found a significant interaction between ICT staff and network technology.[1)]

Our study adds to the research on this topic by providing firm-level evidence for the Netherlands. We replicated the different specifications used in Van Reenen et al. (2010) and compared the results. Moreover, we slightly extended their analysis by estimating an encompassing model of which the other specifications are special cases. Moreover, as sales per worker is used to measure labour productivity, we controlled for intermediate input. In this way, the results can be given an interpretation of correlations with total factor productivity instead of sales per worker.

We started by using proxies for different types of ICT, following the Van Reenen study. However, there is additional information on ICT investment and expenditures available from a recent survey by Statistics Netherlands. As part of this study we investigated whether this information can be used to improve the regression specifications. With its primary intention of providing estimates of aggregate figures on ICT investment for the national accounts, it is the first time that these data are used for economic research. We show how investment ratios can be determined by linking the survey to production data, and how they can be used to determine the relation of various kinds of ICT (computers, communication equipment, purchased/own account software) with productivity. The findings from the resulting first-difference specification are compared to those from the original model.

Although the results of our study do not necessarily imply a causal relation between ICT and firm-performance, they provide insight in the differences in ICT investment among firms, and the way these differences are associated with their productivity. As far as we know, this is the first piece of evidence on this issue specifically for the Netherlands.

The chapter is organized as follows. Section 2 discusses the model and section 3 the operationalization in terms of data and variables. Section 4 presents the estimation results and implied contributions to productivity. Section 5 gives the conclusions and suggestions for further research.

1) Yet another line of research has attempted to explain productivity by specific instances of ICT. Engelstätter (2011) and Van Leeuwen and Polder (2013) for example introduce various types of software (Enterprise Resource Planning, Customer Relationship Management, Supply Chain Management) into a production function. These studies deviate from the ones cited in the main text, however, in that they parameterise the total factor productivity term by ICT, rather than trying to breakdown ICT capital in different types.

4.2 Model

The production technology for each firm *i* in year *t* is described by a Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} M_{it}^{\gamma}$$

where *Y* is output, *K* is capital input, *L* is labour input, *M* is intermediate inputs, and *A* is an efficiency parameter, sometimes labelled total factor productivity.
In its logarithmic form, and expressing the left-hand side in terms of labour productivity, we obtain

$$\ln(Y_{it}/L_{it}) = \alpha \ln(K_{it}/L_{it}) + \gamma \ln(M_{it}/L_{it}) + (\alpha + \beta + \gamma - 1) \ln L_{it} + \varepsilon_{it}$$

where $\varepsilon_{it} \equiv \ln(A_{it}) = c + \omega_{it}$, and *c* is a constant term (reflecting average productivity) and ω_{it} is a stochastic disturbance term.

We are interested in the differential effect of ICT capital *IT* versus non-ICT capital *NIT*, and moreover, in the differential effect of different types of ICT capital, in particular computers *COMP*, networks *NET*, and software *SOFT*. Within software, we distinguish between purchases software *PSOFT* and software developed in own-account *OSOFT*. Thus, the full specification is

$$\begin{aligned} \ln(Y_{it}/L_{it}) = {} & \alpha_1 \ln(NIT_{it}/L_{it}) + \alpha_2 \ln(COMP_{it}/L_{it}) + \\ & \alpha_3 \ln(NET_{it}/L_{it}) + \alpha_4 \ln(PSOFT_{it}/L_{it}) + \alpha_5 \ln(OSOFT_{it}/L_{it}) + \\ & + \gamma \ln(M_{it}/L_{it}) + (\alpha + \beta + \gamma - 1) \ln L_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where $\alpha = \alpha_1 + \ldots + \alpha_5$. We discuss the operationalization in terms of variables in the data section. Since we do not have the stock measures for the various types of capital available, proxies are used following a similar specification in Van Reenen et al. (2010, equation 21).[2) This also allows us to compare our results to theirs. Neglecting intermediate inputs, Van Reenen et al. implicitly put $\gamma = 0$; we also estimated a specification where intermediates inputs are included.

Additional information on ICT investment and expenditures is available from a recent survey by Statistics Netherlands. As part of this study we investigated whether this information can be used to improve the estimations. In the appendix, we show how investment ratios can be determined by linking the survey to production data, and that those can be used to determine the relation of various kinds of ICT – computers, communication equipment (*COMM*), purchased/own account software – with productivity.[3) The resulting specification is a first-difference type model:

$$\begin{aligned} \Delta \ln Y_{it} = {} & \alpha \Delta \ln NIT_{it} + \rho_1 \frac{ICOMP_{it}}{Y_{it}} + \rho_2 \frac{ICOMM_{it}}{Y_{it}} + \rho_3 \frac{IPSOFT_{it}}{Y_{it}} + \rho_4 \frac{IOSOFT_{it}}{Y_{it}} + \\ & \beta \Delta \ln L_{it} + \gamma \Delta \ln M_{it} + \Delta \varepsilon_{it} \end{aligned} \tag{2}$$

2) Note that in the explanation of the equation, Van Reenen et al. seem to distinguish three types of ICT capital (hardware, and purchased/own-account software), while in the estimation results they make an additional distinction between computers and networks.

3) We do not observe investment in network technology, hence this category is excluded. However, we do observe investment in communication technology, which is included here, although it is important to note that this does not include networks.

where the Δ refers to a differenced variable, and the prefix I refers to investment. It should be noted, as explained in the appendix, that the ρ's are the marginal products of the ICT variables, not the output elasticities as the α's in (1).

4.3 Data and variables

Data sources

Our data are sourced from three surveys conducted by Statistics Netherlands: the E-commerce (or ICT) survey, the production statistics (PS), and the ICT expenditure survey. All surveys used in this research are sampled, based on the Business Register of Statistics Netherlands. Not only is the business register exhaustive, it also makes it easy to link enterprises according to their statistical ID. Of course, due to different sampling schemes and different sample sizes, the combined sample is lower than that for each individual survey. The ICT expenditure survey is available for 2009 to 2011. At the time of constructing the data, the most recent year available for the PS was 2010, hence we restrict the sample period to 2009 and 2010. The number of enterprises participating in all surveys is 4,340 in 2009 and 4,522 in 2010.

The E-commerce survey is an annual survey aimed at collecting information on the use of ICT technology and e-commerce in enterprises. Production statistics contain information on the production structure at the firm level. The ICT expenditure survey was set up as a pilot within a Eurostat framework. Due to the voluntary nature of the survey not all member states participated: 14 in 2009 and 10 in 2011. In 2010, no European-wide survey was held, but it was continued nonetheless in the Netherlands. Results from these surveys have been used to construct ICT investments and expenditures at the industry level. Currently, there are no plans to continue the pilot survey at Statistics Netherlands, nor are there any plans by Eurostat. We use the data to assess their value for micro-data analysis.

The survey covers six categories of ICT expenditures. These are listed in table 4.3.1. For all variables both total expenditure and the investments associated with those expenditures are available for 2009. That is, the survey distinguishes between the parts of expenditures that are and are not activated. For the 2010 survey questions on own-account software were left out. Small enterprises were excluded from the survey and only enterprises with 10 or more persons employed were included. The industries agriculture, mining and quarrying, and other personal services were not surveyed. Also public administration was excluded from the survey. In all, a total of 6,649 enterprises responded in 2009 and 6,606 in 2010.

By making use of supply and use tables from national accounts we constructed industry deflators for gross production and sales and intermediate use for 113 separate industries. In addition, we deflated ICT investments and total capital inputs by making use of price information on gross fixed capital formation at the industry level. The asset deflators are available for 56 industries. All deflators have 2008 as their base year.

4.3.1 Variables in the ICT expenditure survey

ICT Product category	Total purchases	Share of investment (out of purchases)	Additional breakdown
Information and communication goods	Question 1	Question 2	– IT goods (1a, 2a) – Communication goods (1b, 2b)
Other ICT goods	Question 3	Question 4	
Software pre-packaged and costumised	Question 5	Question 6	
Software own-account	Question 7	Question 8	– Labour input in own-account SW (7a)
Information and communication services	Question 9	Question 10	– Telecommunication services (9a, 10a)
ICT lease	Question 11	Question 12	– Operating lease or rental services (11a, 12a) – Financial lease (11b, 12b)

Source: Statistics Netherlands.

Variables

Table 4.3.2 lists our measures and proxies used in the analysis. In our model we use deflated sales as the dependent variable.[4)] For intermediate inputs we included all costs except personnel costs. Labour in our model is defined as the number of persons employed. We extracted this variable from the business register to avoid any differences between the employment measurement in the different surveys. As a measure of capital input we used the depreciation cost of fixed assets. Although it does not cover all categories of the user costs of capital, it is the main component and it can be expected to correlate strongly.

For ICT inputs, we include two types of measures for each type: proxies from the e-commerce survey and expenditures from the ICT expenditure survey.[5)] The proxies follow those used by Van Reenen et al. They distinguish hardware, networks, own-account software and purchased software, which are proxied respectively by the percentage of workers with a computer within an enterprise, a network index, software index, and ICT staff as a percentage of total employment. The network index indicates the presence of a LAN with solid lines and/or a wireless network. The software index indicates the use of ERP (Enterprise Resource Planning) and/or CRM (Customer Relationship Management) systems. Both indices have a two-point scale; it should be noted that Van Reenen et al. are able to distinguish more categories.

For all categories, we used the expenditures/investments in our alternative specification, except for networks for which expenditure data is unavailable. Instead we used investment in communication equipment, although it should be noted that network and communication equipment are different asset types. Some of the expenditure categories were only available in 2009, so that the estimation sample is restricted accordingly when these are included.

4) This means that we also include the value of goods for resale. The same applies to intermediate consumption, here the value of the goods for resale is also included.

5) In the expenditure survey we have both the total amount of purchases and the amount of those purchases labelled (by firm) as investment, i.e. to be activated. However, we should note that there is a difference between accounting (where a firm can choose to activate an investment or not) and the conceptual definition of investment. The result is that the share of investment sometimes seems implausibly low in the survey. Therefore, we choose to use the total of purchases because conceptually all those purchases should be seen as an investment (i.e. they will be used in the production process for more than one period).

4.3.2 Overview and description of variables

Variable	Source	Description	Reference period
Sales	PS	Turnover value (including value of goods for resale)[2]	2008, 2009 and 2010
Capital	PS	Depreciation of fixed assets[2]	2008, 2009 and 2010
Intermediate consumption	PS	All costs (excluding personnel costs and including value of goods for resale)[2]	2008, 2009 and 2010
Labour	BR	Employees[1]	2008, 2009 and 2010
PC users	EC	Computers[3]	2008, 2009 and 2010
ICT staff	EC	ICT staff[3]	2008, 2009 and 2010
Software index	EC	Indicates the presence of a CRM and/or ERP system[4]	2008 and 2009
Network index	EC	Indicates the presence of a LAN and/or wifi network[4]	2008 and 2009
Investment in computers	IE	Purchases of computers[2]or[4]	2009 and 2010
Investment in communication equipment	IE	Purchases of communication equipment[2]or[4]	2009 and 2010
Investment in software (purchased)	IE	Purchases of prepackaged software[2]or[4]	2009 and 2010
Investment in own account software	IE	Costs of own account software development[2]or[4]	2009

Source: Statistics Netherlands.
[1] Total number.
[2] In thousand euro.
[3] Percentage.
[4] Categorical variable.
N.B. PS: Production Statistics, BR: Business Register, IE: ICT Expenditure survey, EC: E-commerce survey.

Descriptive statistics

Our combined sample consists of a little over 4,000 units per year. Table 4.3.3 provides the summary statistics for the variables used in the analysis.

4.3.3 Descriptive statistics 2009-2010

	Units	Mean	Standard deviation
Sales	**x 1,000 euros**	56,168	315,038
Intermediate consumption	**x 1,000 euros**	41,951	288,791
Capital	**x 1,000 euros**	1,623	10,036
Labour	**Number of workers**	192	850
PC users	**% of total employment**	0.67	0.34
ICT staff	**% of total employment**	0.04	0.14
Software index	**Presence of technologies**	0.64	0.77
Network index	**Presence of technologies**	1.31	0.65
Computer purchases	**% of total sales**	0.09	8.56
Communication equipment	**% of total sales**	0.01	1.21
Software purchases	**% of total sales**	0.02	1.11
Own-account software	**% of total sales**	0.00	0.01

Source: Statistics Netherlands.

The share of employees working with a PC is quite high: on average two-thirds. The share of ICT staff, on the other hand, is quite low, with 4 percent of total employment. Both the network index and software index indicate the presence of the relevant technologies on a 2 point scale. A majority of firms have at least one network technology in place, while most firms have no more than one of the software types considered (ERP or CRM). Investment in the four different types of ICT capital is quite small in relation to sales, ranging from an average of 9 percent for computers to nearly zero percent for own-account software. Table 4.3.3 also includes summary statistics for the variables sales, intermediate consumption, capital costs (all in 2008 prices) and persons employed. To assess these figures we compare them to the summary statistics of the full PS sample (i.e. before linking to the other sources), as provided in table 4.3.4. We include only those industries which are also in the sampling frame of the ICT-expenditure survey, except financial institutions which are not included in the Production Statistics, and likewise we exclude smaller enterprises. We report unweighted and sample weighted averages (i.e. scaled up to the population totals using sampling weights). Comparing to the PS sample, it is clear that the estimation sample shows higher means. This is due to the fact that the larger enterprises are overrepresented because they are integrally surveyed, besides smaller ones dropping out because of different sampling schemes from each different survey. Comparing both tables provides some intuition about the bias introduced by the overrepresentation of larger enterprises. On average, firms in the estimation sample have sales that are 20 million (54 percent) higher and employ 79 more workers (70 percent). These differences are not negligible, meaning that the results from the regression pertain predominantly to larger enterprises.

4.3.4 Descriptive statistics for Production Statistics sample 2009-2010

	Units	Unweighted mean	Standard deviation	Weighted mean	Standard deviation
Sales	x 1,000 euros	33,374	238,320	36,491	239,218
Intermediate consumption	x 1,000 euros	25,355	216,692	27,475	217,882
Capital costs	x 1,000 euros	983	11,546	1,086	12,112
Persons employed		97	550	113	552
Average number of enterprises per year		26,999	.	50,375	.

Source: Statistics Netherlands.

4.4 Estimation and results

Specifications

We estimated several specifications based on the estimating equations set out in section 2. Table 4.4.1 and 4.4.2 summarise where the specifications differ. Model I, as displayed in table 4.4.1, is similar to that used by Van Reenen et al. (2010). Specification (a) to (d) aim to replicate their estimation results for the Netherlands, using proxies similar to the various types of ICT. The dependent variable is log sales per worker. We tested two additional specifications for model I: specification (e) combines (a) to (d) and takes on board all types of ICT; specification (f) includes intermediate consumption to correct for its effect on gross output-based productivity. All estimations include industry dummies and, where 2009 and 2010 are included, a year dummy, although they are not reported.
Model I uses proxies for the stocks of various types of capital, as the latter are not directly observed. However, using the ICT expenditure survey, we have measures of ICT investment. Section 4.2 shows that under some assumptions the investment ratios can serve as a proxy for the change in capital stock, and a specification in log differences can be used; this is

Model II. As displayed in table 4.4.2, specification (a) and (c) of Model II use current and lagged investment respectively, according to the assumption that investments do or do not become productive immediately. Specification (b) and (d) are similar but add own-account software. Recall from section 4.2 that in Model I the coefficients are output elasticities (γ), whereas in model II the marginal products of ICT capital are estimated (ρ). Finally, in specification (e) we included investment dummies rather than the continuous variables, to investigate the possibility that it is the extensive margin of investment (that is whether a firm has invested in the various types of IT or not) rather than the investment intensity that is related to the productivity differences.[6)]

4.4.1 Specifications of Model I

	Hardware		Software	
Dependent variable (in logs)	computer	communication equipment	own-account	purchased
a Sales per worker	PC users [1)]			
b Sales per worker	PC users [1)]	Network index		
c Sales per worker	PC users [1)]		ICT staff [1)]	
d Sales per worker	PC users [1)]			Software index
e Sales per worker	PC users [1)]	Network index	ICT staff [1)]	Software index
f Sales per worker (controlling for intermediate inputs)	PC users [1)]	Network index	ICT staff [1)]	Software index

Source: Statistics Netherlands.
[1)] Share in total employment.

4.4.2 Specifications of Model II

Dependent variable (in log difference)	**Measure for various types of ICT capital[1)]**
a Sales	Ratio of total expenditures to sales (excluding communication equipment)
b Sales	Ratio of total expenditures to sales
c Sales	Ratio of total expenditures to sales (lagged, excluding communication equipment)
d Sales	Ratio of total expenditures to sales (lagged)
e Sales	Dummies for non-zero total expenditures

Source: Statistics Netherlands.
[1)] Categories are according to model I: computers, communication equipment, own-account software and purchased software.

Regression results using proxies for ICT

The results for Model I are reported in table 4.4.3. Looking at model I and specifications (a) through (e) we find positive effects for hardware which are all around the same size, with coefficients between 0.13 and 0.17. Adding the individual ICT types (specification (b) to (d)), we see that software and networks are significant and positive, while own-account software (ICT staff) is insignificant. Including all types of capital (specification (e)), does not significantly affect the individual coefficients.

[6)] We also estimated Model II using changes in the proxies used in Model I in place of changes in capital stock. However, this did not yield any significant results.

4.4.3 Estimation results of Model I

Dependent variable: log sales per worker	a	b	c	d	e	f
Number of employees[1]	−0.01	−0.03[2]	−0.01	−0.04[2]	−0.04[2]	0.01
Capital per worker[1]	0.28[2]	0.28[2]	0.27[2]	0.28[2]	0.27[2]	0.07[2]
PC users (% of total workers)[1]	0.16[2]	0.14[2]	0.17[2]	0.13[2]	0.13[2]	0.00
Network index		0.06[2]			0.05[3]	−0.02[4]
ICT staff (% of total workers)[1]			0.04		−0.05	0.12[3]
Software index				0.08[2]	0.07[2]	0.02[2]
Intermediate consumption per worker[1]						0.66[2]
Industry dummies	yes	yes	yes	yes	yes	yes
Year dummies	yes	no	yes	no	no	no
Number of observations	8,202	4,018	7,939	4,018	3,755	3,755
R-square	0.48	0.48	0.48	0.48	0.48	0.91

Source: Statistics Netherlands.
1) In logs.
2) Significant at 1%.
3) Significant at 5%.
4) Significant at 10%.

The picture changes when turning to specification (f), where we control for intermediate inputs with an eye on the fact that gross output is used as the dependent variable. Van Reenen et al. do not include this control. However, this is preferable when one is interested in (total factor) productivity. Firstly, we note that in contrast to specification (e) we find no decreasing returns to scale for labour. Moreover, the coefficient on capital decreases substantially. In specification (a) to (e) this coefficient seems a bit high, whereas in (f) it is more in line with rule of thumb estimates of the cost share of capital.[7] Using a similar specification, Atrostic and Nguyen (2007) reported a similar magnitude for the capital coefficient of between 0.08 and 0.09. The contribution of computers goes to zero and becomes insignificant; purchased software still has a positive contribution but its magnitude is much smaller at 0.02. Surprisingly, the network index becomes negative, although only significant at the 10 percent level. The ICT staff coefficient is now the largest of all types and significant. Interestingly, own-account software is thus positively related to productivity, while other types of ICT capital seem to correlate stronger with sales per worker.

Focussing on specification (e) and (f), we see that there are differences in the estimated effects for the different ICT types. A 1 percent increase in computers is associated with a 0.13 percent increase in sales per worker, but not with a productivity increase. Own-account software is not associated with an increase in sales per worker but a 1 percent increase raises productivity by about 12 percent. Adding an additional network technology is associated with an increase of 5 percent (exp(0.05)) of sales per worker, but a 1 percent (exp(0.02)) decrease of productivity. Adding one of the software types is associated with an increase in sales per worker of just over 7 percent (exp(0.07)), and an increase of productivity of about 1 percent (exp(0.02)). The differences in the magnitude of the estimated effects suggest that it is worthwhile to distinguish these different ICT inputs.[8] Moreover, there are differences between the effects on sales per worker and productivity. Our results are roughly comparable to the results by Van Reenen et al. (2010) when we do not account for intermediate inputs. Their estimated elasticity of ICT capital varies from

7) Under neoclassical assumptions, the capital elasticity should be equal to the share of the user cost in total production cost. Roughly, the cost share of capital cost (excluding ICT) is around 10 percent on average, thus suggesting a slightly below normal return to non-ICT capital in our results.
8) Note that it only makes sense to compare the coefficients on the continuous variables and the coefficients on the indices separately.

0.13 to 0.23, which is of a comparable order of magnitude as our estimates. Estimates for purchased software are insignificant in their study, where we find a significant effect. Own-account software is significant in their study; we find a comparable effect in the productivity equation but not in the sales per worker specification. Their estimates for network technology are also positive and significant, although higher than ours. It should be mentioned that the data used by Van Reenen et al. covers more years and countries, so that time or country specific effects (though controlled for) could affect the comparison. In addition, the software and network indices include more categories.

The more important thing to note, however, is the effect of controlling for intermediate inputs. In our case, this changes the results substantially, with ICT capital becoming insignificant and putting much more weight on the effect of ICT staff. Using a gross output specification it seems wise to control for intermediate inputs, and the fact that it seriously affects both the quantitative and qualitative results for the Dutch data, suggests that interpreting the LSE results as productivity effects (rather than on sales per worker) can be misleading.

Regression results using ICT investment data

The results for Model II are given in table 4.4.4. Model II makes use of actual ICT investment data, instead of proxies for ICT user cost. Also, as the specification is in first differences, it controls for unobserved heterogeneity among firms. As is common with first-difference estimators, however, the results are unfortunately somewhat problematic. To start with the output elasticities, we found a rather low estimate on labour input, which also resulted in a strong decreasing return to scale. This finding is robust over the different specifications though. It is also striking when looking at specifications (a) and (b), that all types of ICT capital are insignificant, except for computers in specification (a), which shows a negative effect, and a positive coefficient for own-account software in specification (b). Allowing for assets to become productive after one year, we checked if there were any effects from lagged investments. Only communication equipment showed positive coefficients, while software was negative. Both computers and own-account software were insignificant.

Recall that the coefficient on the ICT types are marginal products and not output elasticities. For completeness, table 4.A.1 in Appendix 2 shows the standardised coefficient for specification (a) to (d) of Model II. While the original coefficients seem to display quite a large variation in magnitude, the standardised coefficients are all of a similar magnitude. A change of one standard deviation in the investment in own account software, for example, is associated with an increase in productivity of about 0.04, while such a change in lagged communication equipment has a similar effect.

The findings of specification (a) to (d) could suggest that one would need to be cautious about the interpretation from the results from Model I, as those results are not robust with respect to controlling for unobserved heterogeneity. However, it is also well-known that first-difference estimators can provide poor estimates, see e.g. Arellano and Bond (1991) and Blundell and Bond (1998). Unfortunately, in our setting we do not have the option to use more advanced estimators.[9] In all, while the results from Model I cannot be

9) For example, most panel data estimators require a longer time-dimension than the one available to us to provide robust estimates. Moreover, recently suggested estimators as the Blundell-Bond (SYS-GMM) and the control function approach as in Ackerberg et al. (2006) start from an equation in levels, whereas we are restricted to the first-difference specification when we want to use the investment data, as set out in section 2.

confirmed by those of Model II using the ICT investment data, we are hesitant to dismiss the conclusions from Model I given the signs that the results of Model II are affected by problems with the first-difference estimator.[10]
The second to last specification (e) provides some support for the notion that the extensive margin also matters. Here we see that switching to investment in both computers and communication equipment is associated with a 1 or 2 percent increase in productivity.[11] However, purchasing software is associated with lower productivity, whereas investing in the development of software on own account is insignificant.

So combining the results from Model I (specification (f)) and II (specification (e)), investing more in tangible ICT capital (computers and/or communication equipment) is not associated with a higher productivity *level*, but firms that invest in computers and communication equipment do show a higher productivity *growth*. Moreover, investing more in *intangible* ICT capital (software) is associated with a higher productivity level, but firms that invest in software show a lower productivity growth. Although seemingly contrasting at first sight, one can think of situations consistent with these results. For example, assume that there are three groups of firms: firms on (or close to) the production frontier, firms at a medium distance from the frontier but with above average productivity, and firms that are far from the frontier with below average productivity. Our findings are consistent with frontier firms investing in intangible ICT capital, the medium group investing in tangible ICT capital, and the bottom group not investing at all. In this scenario, the frontrunners invest in intangibles but it is difficult to achieve productivity beyond the frontier. Thus, investing in software is

4.4.4 Estimation results of Model II

Dependent variable: log difference sales	a	b	c	d	e
Capital[1]	0.06[4]	0.05[4]	0.06[4]	0.06[4]	0.05[4]
Number of employees[1]	0.08[4]	0.09[4]	0.07[4]	0.07[4]	0.08[4]
Intermediate consumption[1]	0.55[4]	0.52[4]	0.57[4]	0.58[4]	0.52[4]
Investment in computers[2]	−0.11[4]	0.24			
Investment in communication equipment[2]	0.17	2.06			
Investment in purchased software[2]	0.20	−0.16			
Investment in own account software[2]		1.00[4]			
Investment in computers[2,3]			−0.02	−0.03	
Investment in communication equipment[2,3]			2.38[4]	4.57[5]	
Investment in purchased software[2,3]			−0.36[4]	−0.38[4]	
Investment in own account software[2,3]				−0.10	
Dummy investment in computers					0.02[5]
Dummy investment in communication equipment					0.01[6]
Dummy investment in purchased software					−0.03[4]
Dummy investment in own account software					−0.01
Year dummy	yes				
Number of observations	4,665	2,215	2,293	2,210	2,585
R-square	0.62	0.56	0.67	0.68	0.57

Source: Statistics Netherlands.
1) In log differences.
2) Ratio to sales.
3) Lagged.
4) Significant at 1%.
5) Significant at 5%.
6) Significant at 10%.

10) We should also mention that while regarding purchases and own account development of software as investments, we do not correct intermediate inputs and production for this. Such a correction is carried out in chapter 1 for industry data for the total of intangible investment. We do not expect this correction to matter much for the results, as purchases of software are small compared to intermediate use and own-account software is small compared to production.
11) For the extensive margin we find no signs of lagged effects of investing in ICT.

associated with higher productivity levels, but firms that invest in software do not achieve a higher than average productivity growth. The middle group is trying to catch-up to the frontier by investing in hardware. The potential productivity gain is higher than for the frontier firms leading to a higher growth; as they have an above average productivity level, investing more in tangible ICT capital will be associated with a higher productivity level. While very tentative, testing this interpretation is an interesting line for further research, as heterogeneity among groups of firms in their investment behaviour poses challenges for policy making.

4.5 Conclusions and further research

Given the heterogeneous nature of ICT, we investigated whether different types of ICT correlate differently with sales per worker and (multi-factor) productivity. We distinguished computers, software (purchased or own-account) and, depending on the specification, networks or communication equipment. Estimating a production function in levels with proxies for the different ICT types (Model I), we found that 1. the estimated effects differ by type of ICT; 2. the effects on sales per worker and on productivity can be different. Computers are associated with higher sales per worker, but not with higher productivity. We found the reverse for own-account software: higher productivity but no difference in sales per worker. Network technology and purchased software associate positively with sales per worker, while the effect on productivity is much lower for purchased software and even slightly negative for networks. So we found that ICT capital is indeed heterogeneous in its relation to firm-performance, in line with Wilson (2009). Our results show, however, that the relation to sales per worker should not be confused with the relation to productivity. A caveat to the results is that they are based on a sample with relatively large firms in terms of sales and employment, and hence the conclusions do not necessarily carry over to the whole population.

We experimented with the use of investment data to improve the estimation. While the measures of ICT investment should in principle be better than the proxies, we can only use them in a first-difference setting (Model II). This does not yield satisfying results in terms of plausibility of the returns to scale and anticipated effects of ICT. For the extensive margin of investment (i.e. whether a firm invests or not), however, we found an indication that computers and communication equipment are associated with higher productivity growth, and software with lower productivity growth. Relating these results to those from Model I, this could be consistent with firms in different parts of the productivity distribution investing in different types of ICT. We recommend this point for further research.

The current study can be regarded as a first attempt to distinguish different types of ICT in a production function framework using linked survey data at Statistics Netherlands. We were able to replicate other international studies, and the results are roughly in line with the existing evidence, although our findings stress that conclusions may depend on the performance measure considered. While the results of using the ICT expenditure data are not all that encouraging, we see various routes to possibly improve the identification of potential effects of ICT in the context of that model.

Firstly, our results were restricted to a limited number of years. It is possible to extend the data period with one year for the ICT expenditures survey and with the more recent production statistics. This would also allow us to investigate in more detail any potential lagged effects of ICT investment.
Secondly, the productivity effect of ICT may depend on co-investment in organizational changes. Hence another line of research could aim for the introduction of measures of such changes into the model.
Thirdly, while we distinguish different types of ICT capital, other capital is assumed to be homogeneous. By linking to the investment survey available at Statistics Netherlands, we could distinguish other forms of capital. This would then allow us to follow the approach by Wilson (2009) more closely, and estimate a model in levels where the different types of investment enter as shares in total investment. We feel this could strongly improve the identification of the different elasticities with respect to our first-difference approach.

Appendix 1. Derivation of the estimating equation for specification using ICT investment data

The ICT expenditure survey offers an alternative route for estimating the structural parameters in equation (1) by making use of investment figures. To economize on notation, we made the point for total ICT investment and presented the full estimating equation with all types of ICT afterwards. First observe that the preferred measure of capital input are the services or user cost of capital. Since these are not directly observed, researchers take a variety of routes to proxy for those services, depending on the data available. In industry studies, such user cost can be derived by using data on investment and making assumptions about depreciation, service life and the rate of return. At the firm level, this is more difficult when longer time-series of investment are missing. In our case, the ICT expenditure survey was available for three years only. Sometimes book values are used as an approximation to capital stock, which are assumed to be proportional to the user cost. In other cases proportionality between investment and capital stock is assumed, and investment is used as a proxy. Problems with the book value measure aside, we do not observe it in our data. Moreover, using investment directly as a proxy for capital stock and services neglects the fact that investment is lumpy and not proportional to capital stock (e.g. Cooper and Haltiwanger, 2006).
Our approach is to rewrite the production function in log differences, and argue that the investment ratio of IT can serve as a proxy for the log difference of IT capital, following Van Leeuwen and Klomp (2006)[12)]

$$\Delta \ln Y_{it} = \alpha_1 \Delta \ln NIT_{it} + \alpha_2 \Delta \ln IT_{it} + \beta\, \Delta \ln L_{it} + \gamma\, \Delta \ln M_{it} + \Delta\varepsilon_{it}$$

The α_2 coefficient is the elasticity of value added with respect to IT capital, which is by definition:

$$\alpha_2 = \frac{\frac{\partial Y}{Y}}{\frac{\partial IT}{IT}} = \frac{\partial Y}{\partial IT}\frac{IT}{Y}$$

12) Van Leeuwen and Klomp (2006) use this trick in the context of knowledge capital. Lacking figures on R&D capital stock, which serves as a proxy to knowledge capital, they use a first-difference specification to be able to make use of R&D investment data. In their paper, they also use a gross output specification. An alternative approach is to use a sample of new firms for which investment is equal to the value of capital stock as in Atrostic and Nguyen (2007), but in our data this would introduce severe selectivity problems.

So the elasticity is the marginal product of IT capital times the IT intensity (i.e. the ratio of IT capital to the value of output). Further, using that $\ln(1 + \alpha) \approx \alpha$, we have that $\Delta \ln IT_{it} \approx (IT_{it} - IT_{it-1})/ IT_{it}$.[13] Putting this together, and defining the marginal product of IT capital as $\rho = \partial Y/\partial IT$, we get

$$\alpha_2 \Delta \ln IT_{it} = \rho \frac{IT_{it}}{Y_{it}} \frac{(IT_{it} - IT_{it-1})}{IT_{it}} = \rho \frac{\Delta IT_{it}}{Y_{it}}$$

Finally, we assume that IT capital accumulates according to the perpetual inventory method,

$$IT_{it} = (1-\delta) IT_{it-1} + IIT_{it} \leftrightarrow \Delta IT_{it} = IIT_{it} - \delta IT_{it-1}$$

where IIT is the investment in IT capital in year t and δ is the depreciation rate. Thus, the change in IT capital is the investment minus the depreciation of the existing stock.
A common assumption to arrive at an estimable production function is then that $\delta = 0$ (or at least small), so that we can use the investment as a proxy for the change in the stock.
In our context, however, assuming that $\delta = 0$ is unfortunate because one can expect a high depreciation on IT goods. Nevertheless, if depreciation is a relatively large component of the change in capital, we can still argue that investment in IT capital is a good proxy for ΔIT_{it}. This is because in this case a high correlation between depreciation and investment is likely, as a large part of the investments will be replacement investments (i.e. replacing the capital that is depreciated). Then investment in ICT capital is still a good proxy for ΔIT_{it}, since it equals the first component and correlates highly with the second. Thus, proxying ΔIT_{it} by IIT_{it}, the estimating equation becomes

$$\Delta \ln Y_{it} = \alpha \Delta \ln NIT_{it} + \rho \frac{IIT_{it}}{Y_{it}} + \beta \Delta \ln L_{it} + \gamma \Delta \ln M_{it} + \Delta \varepsilon_{it}$$

Note that α and γ are the output elasticities the respective inputs, while ρ should be interpreted as the marginal product of IT capital. Moreover, besides enabling us to use investment data, the advantage of using the log difference equation is that it can be thought to control for unobserved heterogeneity. That is if $\varepsilon_{it} = \mu_i + \omega_{it}$ where μ_i is a time-invariant error component, a specification in differences implicitly controls for this fixed effect. This makes the results robust to any possible omitted time-invariant variables and time-invariant measurement error.

Reintroducing various types of ICT capital gives equation (2):

$$\Delta \ln Y_{it} = \alpha \Delta \ln NIT_{it} + \rho_1 \frac{ICOMP_{it}}{Y_{it}} + \rho_2 \frac{ICOMM_{it}}{Y_{it}} + \rho_3 \frac{IPSOFT_{it}}{Y_{it}} + \rho_4 \frac{IOSOFT_{it}}{Y_{it}} +$$

$$\beta \Delta \ln L_{it} + \gamma \Delta \ln M_{it} + \Delta \varepsilon_{it}$$

Note that firm growth in year t is being related to investment in year t. This follows from the equation determining the accumulation of capital, where current capital stock is the sum of existing capital stock after depreciation and current investment. It is sometimes assumed that capital takes time-to-build, and becomes effective only after a period of time (e.g. Kydland and Prescott, 1982). That is, there is a lag between the timing of the investment and the time when it becomes productive, for example due to the time needed for installation, testing new equipment, or the need for workers to learn how to operate the new technology. Although there are likely to be differences between different kinds of capital in this respect as well, it is easy to accommodate a one-period lag for capital to

[13] Note that the approximation of $\ln(1+\alpha)$ by α holds for small α. In our case $\alpha = \Delta IT_{it}/IT_{it}$ hence this implies that the approximation works well when the change in IT stock is small compared to the existing stock.

become productive. In this case investment should be replaced by its lag, i.e. the ratio of lagged investment to current output is used.

Appendix 2. Standardised coefficients for Model II with ICT investments

4.A.1 Standardised coefficients of Model II

Dependent variable: log first difference sales	a	b	c	d
Investment in computers[1]	−0.03[3]	0.01		
Investment in communication equipment[1]	0.00	0.02		
Investment in purchased software[1]	0.01	−0.01		
Investment in own account software[1]		0.04[3]		
Investment in computers[1][2]			0.00	0.00
Investment in communication equipment[1][2]			0.03[3]	0.03[4]
Investment in purchased software[1][2]			−0.03[3]	−0.03[3]
Investment in own account software[1][2]				−0.01

Source: Statistics Netherlands.
1) Ratio to sales.
2) Lagged.
3) Significant at 1%.
4) Significant at 5%.
5) Significant at 10%.

5.

E-commerce and competition

The internet has a profound impact on the way firms organise their business and deal with their customers. E-commerce is thought to have increased market competition. We investigated this issue, and found evidence that this is indeed the case for Dutch firms. The effect turned out to be strongest in the services sector. Increasing competition, however, may stimulate product innovation, but it does not increase the probability of a firm adopting e-commerce.

5.1 Introduction

The rise of the internet and in particular the advent of e-commerce is thought to reduce price dispersion as a result of lowering search costs of consumers and ‘menu cost’ of retailers (B2C trade) or suppliers (B2C and/or B2B trade). So if e-commerce activities of firms increase, price competition could be fiercer, and demand could be more elastic, which in turn could lead to a change of the supply side market structure (see e.g. Goldmanis et al., 2009). However, much research on the role of e-commerce for competition is based on case-studies for more or less specific examples of trading goods. Typically, such research has been focused on the price differentials for one homogeneous product, e.g. the same book, the same CD or the same life insurance policy. Although we recognise that the emergence and spread of the internet for firm performance in general has invoked a lot of valuable research, most studies do not go beyond a statistical description of price differentials for goods that are comparable in almost all features, except for being sold via two alternative distribution channels. Moreover, the degree of competition is also likely to affect innovation and/or the adoption of new technologies. So there may be feedback effects running from competition to engaging in e-commerce which are unaccounted for in the existing empirical literature.

The mainstream of empirical research on competition builds on the well-known Hall framework (Hall, 1986, 1988). In general, the focus in this framework is on the reduced-form estimation of productivity models with market conditions taken into account in some way. Two routes are open to assess the level of competition in this framework:

1. estimating demand parameters simultaneously with the ‘true’ technology parameters of production functions;
2. confronting estimates of production elasticity with revenue shares.

A distinction between the two approaches is that from 1. we derive a market-wide competition parameter, while in principle 2. allows us to capture heterogeneity in the degree that firms are subject to competition through the estimation of so-called mark-ups (i.e. the ratio of prices over marginal costs). Nevertheless, we are unaware of examples of applications of the Hall framework that discuss the role of innovation or the application of new ICT for competition.

Considering the above, a more general treatment of the relationship between e-commerce and competition, or how e-commerce affects the competitiveness of firms, is still lacking. This study tries to fill the gap by using a rich panel data set constructed after linking three surveys: on ICT usage, innovation and business structure characteristics. We used this dataset to investigate whether innovativeness (and in particular e-commerce as an instance of IT innovation) affects competition, and vice versa. The Hall framework seems a good a starting point even though output prices may differ between firms for other reasons than being involved in e-commerce, and price differentials may not be the only reason why consumers prefer the internet for buying goods or services. We derived firm-level mark-ups from the estimation of a production function, following De Loecker and Warzynski (2012), and subsequently analysed the evolution of these mark-ups with the help of indicators on the firms' intensity of engaging in e-commerce. Moreover, we explored a more general model where competition affects the adoption of new technologies (among which e-commerce), where adoption of these innovations influence productivity and, indirectly, the mark-ups.

The chapter starts by presenting the theoretical reasoning behind our application in the next section. Section 5.3 discusses the available data, the empirical implementation and the results obtained so far, and we close with several conclusions.

5.2 Data

For analysing the relationship between e-commerce and competition we constructed a comprehensive dataset by linking three surveys:

a) The Production Statistics Survey (SBS panel), which covers the years 2000–2010. This survey contains firm-level data on employment, gross output, turnover, value added and intermediate inputs of firms. After matching with industry-level deflators, this source can be used to construct different output measures such as value added and gross output productivity, profitability and revenue shares;
b) The survey on ICT usage of firms (e-commerce survey, IT panel) for 2002–2010. This survey is used to obtain data on the state of internet usage, various types of connections in use, the adoption of ICT-related innovations and the occurrence and intensity of electronic selling (e-sales) and electronic procurement (e-buying);
c) The Community Innovation Surveys (Innovation panel) for 2002–2004, 2004–2006, 2006–2008 and 2008–2010. For the extension of our model, this survey is used to obtain data on the various types of innovation adopted, the R&D inputs into (technological) innovation and other variables, such as dependence on foreign markets, innovation subsidies received from different bodies and innovation cooperation.

5.3 Competition and the adoption of e-commerce

Not only does ICT affect the nature and degree of competition, it can also be hypothesised that competition impacts on the adoption of new technologies. Being innovative is one of the ways through which firms can escape competition (e.g. Aghion and Griffith, 2008). To investigate this possibility, we therefore estimated a multivariate adoption equation with different types of innovation, namely product, process, organizational innovation as well as the occurrence of e-commerce, defined as a firm engaging in either e-selling or e-buying. The reason for investigating the adoption of e-commerce together with other types of innovation is that in earlier work (Polder et al., 2010a) we found that the adoption decisions are strongly correlated, possibly because of mutual complementarities. For this analysis, we merged our SBS-IT panel with the innovation data to obtain the SBS-IT-innovation panel.

5.3.1 Developments in competition by sector

	2000–2005	2006–2010
Manufacturing		
Number of firms	41,316	29,530
Number of firms weighted	145,421	98,016
Profit elasticity		
average	−4.770	−4.268
average (weighted)	−4.810	−4.386
minimum	−7.729	−7.717
maximum	−1.613	−1.415
Construction		
Number of firms	28,804	22,608
Number of firms weighted	170,309	216,089
Profit elasticity		
average	−2.894	−2.985
average (weighted)	−3.520	−3.459
minimum	−4.233	−4.660
maximum	−2.015	−1.901
Trade		
Number of firms	74,136	54,895
Number of firms weighted	708,602	407,394
Profit elasticity		
average	−2.949	−3.206
average (weighted)	−3.297	−3.478
minimum	−4.586	−4.000
maximum	−0.884	−1.576
Other commercial services		
Number of firms	71,138	67,167
Number of firms weighted	529,705	533,987
Profit elasticity		
average	−2.094	−2.098
average (weighted)	−1.983	−2.123
minimum	−3.992	−4.239
maximum	−0.935	−0.577

Source: Statistics Netherlands.

We opted for the use of the profit elasticity (PE), introduced by Boone (2008) to measure competition. As explained in chapter 1, this indicator describes the relation between a firm's profit and its marginal costs. It is defined as the percentage change in (variable) profits due to a one percentage change in marginal costs (i.e. the elasticity of profit with respect to marginal costs). The reasoning behind this indicator is that the elasticity of profit with respect to costs will be higher in highly competitive markets than in less competitive markets. The PE can only be calculated with the help of micro-data, but it can be determined for different industries (markets) and years separately. Following Boone et al. (2007) and Van der Wiel (2010), the profit elasticity is calculated as the regression coefficient in the regression

$$\ln(R_{it} - VC_{it}) = -\beta_t \ln(MC_{it}) + \nu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

with R denoting profits, VC total variable costs (both available in the data), MC marginal costs, ν a firm-specific fixed effect, λ a year dummy and ε an (idiosyncratic) disturbance term. This regression can be carried out separately for each industry and each year, after using data on average variable costs as a proxy for unobserved marginal costs, and with the help of a panel data estimator, that controls for firm-specific fixed effects.

In this exercise, it is not trivial to have a sound delineation of markets. This is a problem that continuously plagues empirical competition research because the available data may not reflect the perception of markets as perceived by individual firms (the real actors on a market, however defined). Following the existing empirical research, we used the standard industrial classifications. The three digit-level of NACE (readily available in the SBS Surveys) is the lowest level of classification that allows for a proper estimate of (1) in terms of number of observations per industry.

We estimated equation (1) in two ways. Firstly, we investigated the differences in the degree of competition over industries and time. Therefore, we applied a spline estimate that covered two periods: 2000–2005 and 2006–2010. The results of these spline panel regressions using the three digit NACE classification are summarised in table 5.3.1. The general picture is that the level of competition is higher in manufacturing than in the other branches considered, although it slightly decreased between 2000–2005 and 2006–2010. By contrast, competition increased slightly in the trade sectors and other commercial services, whereas in construction it remained the same in the two periods considered. Because the emergence and spread of e-commerce in the second part of our sample period may be more relevant for firms in trade and other business services, the observed increase in competition reinforced our motivation for looking at the impact of e-commerce on competition, and also at the differential impact between industries.

5.3.2 Estimation results innovation adoption model

	Product innovation		**Process innovation**		**Organizational innovation**		**IT innovation**	
# obs = 12,297 (2003–2010)	coeff	se	coeff	se	coeff	se	coeff	se
Variable								
Profit elasticity	0.016	0.008[2]	−0.007	0.008	−0.015	0.007[1]	−0.014	0.007[2]
Part of enterprise group	0.098	0.040[1]	0.067	0.039[3]	0.189	0.034[1]	0.006	0.033
Part of foreign company	0.004	0.037	−0.080	0.034[2]	0.028	0.030	−0.018	0.031[1]
Firm is exporter	0.198	0.033[1]	0.171	0.033[1]	0.198	0.028[1]	0.247	0.028[1]
Involved in innovation cooperation	1.049	0.035[1]	0.904	0.033[1]	0.687	0.029[1]		
R&D subsidies received	0.548	0.043[1]	0.401	0.038[1]				
Broadband connectivity (lagged)	0.332	0.047[1]	−0.070	0.046	0.310	0.039[1]	0.578	0.039[1]
Performs R&D on permanent basis	1.291	0.043[1]	0.448	0.038[1]				
Employment (lagged in logs)	0.049	0.012[1]	0.079	0.011[1]	0.174	0.010[1]	0.144	0.009[1]
Log Likelihood	−25,354.2							

Estimations include year and industry dummies.
1) Significant at 1%.
2) Significant at 5%.
3) Significant at 10%.
Source: Statistics Netherlands.

Secondly, we pooled the data for each industry over years and estimated (1) with the help of a fixed-effect panel estimator, allowing the coefficient β to vary across all years. We used the obtained Boone indicator in the estimation of an innovation adoption model, which is a multivariate probit, extending the model used in Polder et al. (2010a) to include IT innovation (defined as having engaged in e-commerce) and profit elasticity as an additional explanatory variable.[1)] The results are presented in table 5.3.2. Note that we did not include the same explanatory variables for all innovation modes. For example, we excluded R&D subsidies received from the specification for organizational and IT innovation, as those subsidies clearly concern technological innovation alone.
In general the results were very similar to our earlier research. Given the significant estimates of the various ICT variables, they underlined the specific role of ICT as an enabler of innovation, and provided evidence that the role of ICT goes beyond the conventional interpretation that ICT is enhancing productivity in a narrow sense. In the context of this chapter, however, our interest mainly concerns the estimated coefficient on profit elasticity. According to our results, more competition is associated with a higher probability of adopting product innovations. But more competition negatively affects the probability of engaging in organizational or IT innovation. The correlation with process innovation is insignificant. This implies that in considering the relation of innovation and competition it would be wise to distinguish different types of innovation. People considering how to stimulate innovation through competition policy, for instance, should realise that increasing competition may not encourage all types of innovation.

5.4 Derivation of mark-ups

We now turn to the investigation of how e-commerce affects competition at the firm-level. Whereas profit elasticity is an industry measure of competition, in this analysis we were after the relation at the firm-level and hence we were in need of a firm-level competition measure. This section explains how to derive so-called mark-ups using production data.
In essence, the mark-up is the relative difference between the price of output and the marginal cost of producing. If competition is fierce, i.e. demand is relatively price elastic, a firm is less able to increase its margins by raising prices than when competition is low, and demand is less sensitive to prices. We used a value-added based production technology with capital (K_{it}) as a fixed input and labour (L_{it}) as a flexible variable input:

$$Q_{it} = A_{it}F(K_{it}, L_{it}; \theta) \tag{2}$$

where A_{it} denotes a (Hicks-neutral) productivity term, related to the concept of total factor productivity (TFP) used in growth accounting practices. This equation is the basis for our estimates explained in section 5.6. However, first we will explain how we derived mark-ups. In doing so, we closely followed the approach by De Loecker and Warzynski (2012). Under cost minimization and absence of adjustment cost, the optimality condition for setting the employment level is

1) See Polder et al. (2010a) section 3.2 for technical details and a detailed description of the explanatory variables used besides competition. We used the Stata module 'mvprobit' developed by Cappellari and Jenkins (2006) for the estimations.

$$\frac{\partial Q_{it}}{\partial L_{it}}\frac{L_{it}}{Q_{it}} = \frac{P_{it}^{L} L_{it}}{Q_{it}} / \frac{\partial C_{it}}{\partial Q_{it}} \tag{3}$$

where P_{it}^{L} is the price of labour, and $C(\cdot)$ is the cost function.
The mark-up μ is defined as the ratio of the output price P_{it} to the marginal production cost[2)],

$$\mu_{it} \equiv \frac{P_{it}}{\partial C_{it}/\partial Q_{it}} \tag{4}$$

Using the optimality condition for labour, an expression for the mark-up is then

$$\mu_{it} = \frac{\partial Q_{it}}{\partial L_{it}}\frac{L_{it}}{Q_{it}} / \frac{P_{it}^{L} L_{it}}{P_{it} Q_{it}} \equiv \theta_{it}^{L} / s_{it}^{L} \tag{5}$$

where θ_{it}^{L} is the output elasticity of labour, and s_{it}^{L} is the ratio of labour cost to the value of total output. So the mark-up can be estimated by obtaining an estimate for the output elasticity and comparing it to the cost share of labour. The latter is directly observed in the data for each firm, while the output elasticity requires the estimation of the production function, which is what we turn to next.

5.5 Empirical strategy

As described at length in chapter 1, simple OLS estimation of – the loglinear form of – equation (2) may not be appropriate. The central issue is that productivity is a firm-specific state variable, only known to the firm and not to the researcher. It may play a role in determining the choices of the level of flexible inputs. So labour input decisions are endogenous, because they depend on an unknown state of productivity. Neglecting this problem may lead to estimates of production elasticity that suffer from endogeneity biases, which in turn in our application may lead to erroneous estimates of mark-ups.

Recent productivity research uses a production function framework that tries to account for this endogeneity bias by including the evolution of productivity states in the model. The most well-known approaches go back to Olley and Pakes (1996) and Levinsohn and Petrin (2003). A more recent contribution to this strand of research, which introduces a refinement of the aforementioned approaches, is given by Ackerberg et al. (Ackerberg, Caves and Frazer (ACF), 2006), applied by De Loecker and Warzinsky (2012) and Doraszelski and Jaumandreu (2013) among others. Following these studies, we will consider the translog production function

$$y_{it} = \beta_0 + \beta_L l_{it} + \beta_K k_{it} + \beta_{LL} l_{it}^2 + \beta_{KK} k_{it}^2 + \beta_{LK} l_{it} k_{it} + \omega_{it} + \varepsilon_{it} \equiv X_{it}\beta + \omega_{it} + \varepsilon_{it} \tag{6}$$

2) As mentioned by De Loecker and Warzinsky, this definition is consistent with most price setting models, see their online appendix.

which relates (log) value added to (log) labour and (log) capital inputs. This is a flexible approximation that allows output elasticities to vary by firm and over time as in equation (5). They are given by

$$\alpha_{Lit} = \frac{\partial Q_{it}}{\partial L_{it}} \frac{L_{it}}{Q_{it}} = \beta_L + 2\beta_{LL} l_{it} + \beta_{LK} k_{it} \tag{7}$$

The more commonly used Cobb-Douglas specification can be obtained by removing the second-order terms (i.e. the squares and interactions) from equation (6). Consequently, the output elasticity is assumed to be constant over firms and time. Nevertheless, mark-ups will still be firm-specific due to the variation in the revenue share of labour.

The main feature of the ACF method concerns the different way of uncovering unobserved productivity states by providing a refinement of the method introduced by Levinsohn and Petrin (2003). Similar to Levinsohn and Petrin, the basic assumption of the ACF method is that productivity shocks are most likely to show up in the demand for intermediate inputs of firms. The difference between the two approaches is that ACF give up the assumption that the output elasticity of labour is identified in a first stage regression.
We briefly discuss the ACF approach; for more details the interested reader is referred to the original paper. Consider the production function

$$y_{it} = f(X_{it}; \beta) + \omega_{it} + \epsilon_{it} \tag{8}$$

where X_{it} is a vector of explanatory variables, including inputs and possible interactions. The source of endogeneity is the fact that the firm has information on its productivity level at the time of deciding on its level of factor inputs, which is summarised in the productivity state ω_{it}. As this term is unobserved by the researcher, it is part of the error structure which causes the input levels to be correlated with the overall disturbance term. Following Olley-Pakes and Levinsohn-Petrin, ACF assume that this term evolves according to a first-order Markov process

$$\omega_{it} = \rho\omega_{it-1} + \xi_{it} \tag{9}$$

where ξ_{it} is the so-called innovation to productivity, which is assumed to be unknown to the firm and uncorrelated to any input levels. The ACF procedure is aimed at teasing out estimates for ξ_{it}, and using the fact that they are uncorrelated to input levels, constructing moment restrictions that allow for Generalized Method of Moments (GMM) estimation.
To control for the unobserved productivity, the levels of flexible inputs can be expressed as a function of the state variable. Relying on intermediate inputs, we therefore have

$$m_{it} = m(k_{it}, \omega_{it}) \tag{10}$$

Assuming invertibility, it follows that the unknown productivity ω_{it} can be written as a function of intermediate inputs m_{it} and the state variables k_{it}. Without assuming a functional form, this inverse function can be approximated by a low-order polynomial h, yielding

$$y_{it} = f(X_{it}; \beta) + h(k_{it}, m_{it}) + \epsilon_{it} = \phi(X_{it}; \theta) + \epsilon_{it} \tag{11}$$

The first-stage of the ACF procedure involves OLS estimation of equation (11). Note that we do not identify the structural parameters at this stage. Having estimates of expected output ϕ, however, we can now write the unknown productivity state as

$$\omega_{it}(\beta) = \hat{\phi}_{it} - X_{it}\beta \tag{12}$$

Moreover, given a value for β, the autoregressive process for ω can be estimated using OLS on equation (9). Then, finally, we have that

$$\xi_{it}(\beta) = \omega_{it}(\beta) - \hat{\rho}\omega_{it-1}(\beta) \tag{13}$$

As mentioned above, ξ_{it} is the innovation to productivity and can be used to construct moment restrictions for GMM estimation:

$$E(\xi_{it}(\beta)Z_{it-1}) = 0 \tag{14}$$

where $Z_{it} = \{l_{it-1}; k_{it}; l_{it-1}^2; k_{it}^2; l_{it-1}; k_{it}\}$, where k_{it} is assumed to be predetermined and hence independent of ξ_{it}. If one is unwilling to make this assumption, one can easily replace capital by its lag. The GMM estimation procedure minimizes a quadratic criterion function based on (14) to estimate β.

The procedure can be easily extended to allow for other determinants to affect productivity. This can be done by including additional terms in the Markov equation (9). For example, De Loecker and Warzynski (2012) include the firm's lagged export status. In our case, we will present in section 5.6 an extension of our model including innovation dummies, among which the adoption of e-commerce.

5.6 Results

Mark-ups

We estimated the mark-ups with the ACF method for different datasets. The most extensive dataset in terms of number of firms covered uses Production Statistics data only (hereafter referred to as SBS panel). Another dataset consists of the firms that are available in the SBS panel as well as in the IT panel (hereafter referred to as the SBS-IT panel). We used this dataset as our basic source for investigating the relation between mark-ups and e-commerce. In the next section we will present an extension of our model that involves linking to the innovation data. We therefore also estimated the mark-ups for that sample (SBS-IT-innovation sample).

In order to have a benchmark, we also estimated the model using OLS. The estimates are carried out at a lower level of aggregation (roughly two-digit industries), to account for intrinsic differences in the production as well as the market structures. Therefore, a myriad of regression results is generated and to keep things tractable, we do not present the full details. These are available on request, and we will focus on the descriptives of the estimated production elasticity and the mark-ups constructed from the estimated labour elasticity.

5.6.1 Summary of OLS and ACF regression results and descriptive statistics

Sample	SBS panel			SBS-IT panel		
	mean	standard deviation	median	mean	standard deviation	median
I) Manufacturing						
Number of observations	33,375	33,375	33,375	7,744	7,744	7,744
Employment in fte's	126.1	313.7	49.3	229.8	434.4	121.7
Gross output per fte in 2000 prices	233.8	361.8	153.2	261.6	357.5	179.1
Value added per fte in 2000 prices	63.6	64.0	51.2	70.2	53.8	57.2
Profit ratio[1]	0.057	0.33	0.051	0.056	0.099	0.050
Labour elasticity OLS Translog	0.793	0.155	0.809	0.795	0.167	0.815
Labour elasticity ACF Translog	0.805	0.313	0.765	0.879	0.366	0.798
Capital elasticity OLS Translog	0.107	0.063	0.099	0.097	0.072	0.087
Capital elasticity ACF Translog	0.286	0.249	0.269	0.238	0.287	0.256
II) Services						
Number of observations	77,746	77,746	77,746	9,795	9,795	9,795
Employment in fte's	108.4	681.2	25.1	275.9	1,103.6	81.5
Gross output per fte in 2000 prices	344.5	1,082.2	144	284.1	739.3	123.8
Value added per fte in 2000 prices	64.3	132.1	47.7	66.6	89.2	49.0
Profit ratio[1]	0.061	1.205	0.464	0.059	0.168	0.044
Labour elasticity OLS Translog	0.762	0.126	0.667	0.762	0.128	0.741
Labour elasticity ACF Translog	0.826	0.292	0.865	0.779	0.378	0.883
Capital elasticity OLS Translog	0.125	0.089	0.115	0.149	0.093	0.137
Capital elasticity ACF Translog	0.278	0.222	0.217	0.320	0.280	0.204

Source: Statistics Netherlands.
[1] Operating surplus (before taxes and exlusive of financial results) as as a percentage of turnover.

Besides summarizing the estimation results, table 5.6.1 also shows some summary statistics for our estimation samples. After matching surveys, we ended up with quite different samples regarding size: for manufacturing as well as for services the (average) firm size was largest for the SBS-IT panel. For the profit ratio, we observed a similar pattern

5.6.2 Descriptive statistics for mark-up estimates

	SBS panel		SBS-IT panel	
	OLS[1]	ACF[2]	OLS	ACF
Manufacturing				
number of firms	33,375	33,375	7,744	7,744
mean	1.174	1.288	1.214	1.492
median	0.853	0.996	1.060	1.058
25th percentile	0.705	0.718	0.864	0.740
75th percentile	1.276	1.360	1.282	1.486
Services				
number of firms	77,746	77,746	9,795	9,795
mean	1.247	1.409	1.024	1.142
median	0.996	1.126	0.893	0.941
25th percentile	0.755	0.725	0.693	0.454
75th percentile	1.347	1.647	1.172	1.426

Source: Statistics Netherlands.
[1] OLS: Ordinary Least Squares.
[2] ACF: Ackerberg-Caves-Frazer GMM estimator.

for manufacturing, but the differences for services firms were less clear. Moreover, the distributions of the profit ratio and the production elasticity were quite similar across samples and between the broad industries considered. The most striking differences for production elasticity concerned the differences between the OLS and ACF capital elasticity. Similar to results of Olley and Pakes (1996), we found a substantial downward simultaneity bias for the OLS capital production elasticity, whereas the ACF results seemed to be more plausible.
A summary of the mark-up estimates for the three panels is given in table 5.6.2. Some interesting conclusions can be drawn from these results. Firstly, the table shows a considerable heterogeneity in estimated mark-ups within sectors, judging from the interquartile range. Secondly, the estimated mark-ups are higher after using ACF, compared to the OLS benchmark equivalents. So it seems that taking into account the endogeneity of the input factors reduces the estimates of the degree of competition (note that the mark-ups are inversely related to competition).

Looking at the results from the largest dataset (SBS panel), competition seems to be stronger in manufacturing than in services, i.e. the average mark-ups are lower in manufacturing. However, a striking result is that the pattern of competition changes when linking to the e-commerce and the innovation data. When we used the firms for which we also had data on e-commerce available (the SBS-IT panel), calculated mark-ups are higher in manufacturing than for services. So in estimating mark-ups we need to be wary of selection effects when samples become smaller. As the firms in the SBS-IT are on average larger, firm size could play a role here. Apparently, larger firms in manufacturing suffer less from competition than those in services, while smaller firms in manufacturing suffer more than their counterparts in services.

E-commerce and mark-ups

The ultimate goal of this research is to assess whether the emergence and spread of e-commerce has changed competition, and in which direction. Having the mark-up estimates available as a measure of competition, the natural way to proceed is to relate (changes) in mark-ups to (changes) in e-commerce practices of firms, controlling for other factors that may explain why mark-ups differ between firms. This section summarises the results of regressions carried out to investigate the relation between (the estimated) mark-ups and e-commerce.

Notwithstanding its growing importance, many firms were not involved in any type of e-commerce even towards the end of our sample period. The distributions for e-commerce variables (either e-sales or e-buying) in the data were still very skewed. The mean value for the share of internet sales in total sales in 2010 was about 5 percent, and 8 percent for the share of e-buying in total purchases in the same year. However, the median value for both variables was zero in 2010, indicating that at least 50 percent of the firms reported that they were not involved in e-commerce. Our mark-up estimates covered the period 2000–2010, whereas data collection on e-commerce started in 2002. Moreover relatively few firms were involved in e-commerce in the first half decade of the century. Therefore, the estimation sample is much smaller than the original SBS-IT sample. We chose to adopt two specifications for explaining the differences in mark-ups:

1. a first-difference (growth) regression that relates the change in mark-ups to the change in the e-commerce intensities and

2. a dynamic panel data (DPD) model for the levels of mark-ups and e-commerce, i.e. the SYS-GMM approach by Blundell and Bond (2000).

Both specifications control for unobserved heterogeneity and time-invariant measurement and specification error (i.e. firm fixed-effects), including selection bias. The latter specification also controls for possible persistency in measurement and specification error.

5.6.3 Relation between mark-ups and e-commerce

Method	A First difference		B First difference		C SYS-GMM[1]	
Dependent variable: log markup	coeff	se	coeff	se	coeff	se
e-commerce intensity	−0.044	0.011[2]				
e-sales (%)			−0.091	0.017[2]		
lagged mark-up					0.685	0.011[2]
e-sales (%)					−0.327	0.072[2]
Number of observations	9,984					

Source: Statistics Netherlands.
1) SYS-GMM: GMM estimation after Blundell and Bond (2000).
All estimations control for industry effects and a time trend.
2) Significant at 1%.
3) Significant at 5%.
4) Significant at 10%.

The results of the first-difference are presented in table 5.6.3. All regressions included a trend and industry dummies as a control. E-commerce was taken into account in two ways: we used the share of e-sales in total sales, as well as a composite indicator which is the sum of the e-sales and e-buying intensity (e-commerce intensity).[3] If a growing penetration of e-commerce increases competition, then we expect a negative sign for the estimate of the e-commerce variables. This is indeed the case in all estimates. The first difference results indicated that an increase of 1 percentage point in the e-sales intensity is associated with a reduction of the mark-ups of 0.1 percent.[4] A similar increase in the e-commerce indicator is associated with a reduction of 0.04 percent. While these results seem to imply a low impact of e-commerce on mark-ups, we noted that the respective standard deviations of e-sales and the e-commerce intensity are 0.15 and 0.25. So a change of one standard deviation leads to a reduction of 1.5 percent and 1 percent, respectively.

The last column of table 5.6.3 shows the results of the so-called ‘system’ dynamic panel data model. We found a significant persistence in the mark-ups, which suggests how appropriate using this approach is. Taking into account this persistence as a source of differences in mark-ups between firms and over time, the impact of the e-sales variable increases compared to the first-difference results. An increase in e-sales of 1 percentage point is associated with an overall decrease of the mark-ups with 0.3 percent, implying a decrease of nearly 5 percent for an increase of one standard deviation.

3) Note that this indicator cannot be interpreted as a percentage: it is the sum of the share of e-sales in total sales and the share of e-purchases in total purchases; as such it can (in theory) range from 0 percent to 200 percent.

4) Note that these are semi-log specifications: the dependent variable (mark-up) is in logs, while the explanatory variable of interest (e-commerce) is not. So a change from p percentage points is associated with a percentage change in mark-up of $(1 - \exp((p/100)\cdot\beta))\cdot 100\%$.

5.6.4 Relation between mark-ups and e-commerce by industry

Method	A First difference		B First difference		C SYS-GMM	
Dependent variable: log mark-up	coeff	se	coeff	se	coeff	se
I) Manufacturing (# obs = 4,449)						
e-commerce intensity	−0.054	0.015[1]				
e-sales (%)			−0.110	0.021[1]		
lagged markup					0.673	0.016[1]
e-sales (%)					−0.039	0.069
II) Trade (# obs = 1,775)						
e-commerce intensity	−0.039	0.019[2]				
e-sales (%)			−0.080	0.032[1]		
lagged mark-up					0.564	0.025[1]
e-sales (%)					−0.412	0.063[1]
III) Other commercial services (# obs = 3,260)						
e-commerce intensity	−0.041	0.024[3]				
e-sales (%)			−0.075	0.038[2]		
lagged mark-up					0.706	0.021[1]
e-sales (%)					−0.553	0.147[1]

Source: Statistics Netherlands.
SYS-GMM: GMM estimation after Blundell and Bond (2000).
All estimations control for industry effects and a time trend.
[1] Significant at 1%.
[2] Significant at 5%.
[3] Significant at 10%.

We close the discussion of our results by looking at a lower level of aggregation. Table 5.6.4 shows the results separately for manufacturing, trade and other commercial services. In general, as in the combined samples, the estimates for e-commerce intensity are somewhat smaller (and less significant) than when using e-sales as an explanatory variable. The estimates in the first-difference regressions are very similar to those in table 5.6.3, ranging from −0.075 (other commercial services) to −0.110 (manufacturing). However, the preferred estimation method ('system GMM', panel C) shows a sharper contrast in results. There the estimates for the e-sales intensity are stronger in trade and in commercial services, whereas we found no significant effect in manufacturing. This suggests that the growing penetration of e-commerce is important for understanding changes in competition patterns, but mainly in the services sector. This is consistent with the fact that e-selling (in particular, business-to-customer, or B2C) is more frequently observed in trade and services than in manufacturing.

Augmenting the production function with innovation and e-commerce

Besides affecting competition, there is also a robust body of empirical evidence that innovation and ICT affect productivity (see e.g. Van Leeuwen, 2008, and references therein). With this in mind, it makes sense to test an augmented version of the production function used for the estimation of the marks. A nice feature of the ACF method is that it allows a richer description of the evolution of productivity states. Recent applications of this approach are Doraszelski and Jaumandreu (2013) and De Loecker and Warzinsky (2012), who respectively investigated the impact of R&D and export behaviour.

The main idea is that the Markov process for the evolution of productivity states can be parameterised as a function of explanatory variables. We followed this approach, using innovation – and IT indicators as inputs into production, as well as for explaining the evolution of productivity states. In practice, this means that we added dummies for innovation and the usage of e-commerce to equation (9), and moreover directly into the production function:

$$y_{it} = \beta_0 + \beta_L l_{it} + \beta_K k_{it} + \delta' D_{it} + \omega_{it} + \varepsilon_{it} \tag{15}$$

$$\omega_{it} = \rho\omega_{it-1} + \vartheta' D_{it-1} + \xi_{it} \tag{16}$$

With an eye on the decrease in the number of observations, we only made a distinction between manufacturing and services. For the presentation, we reported the results for the more parsimonious Cobb-Douglas specification (i.e. interactions and squares in equation (5) were ignored).[5] The translog results are highly similar, and will be used to calculate new mark-ups. From this augmented specification we can assess the magnitude and direction in which innovation and e-commerce affect productivity (directly and through its effect on the lagged productivity states), and moreover, how this affects the mark-up estimates: does taking new technologies into account increase or decrease the estimated competition?

5.6.5 Estimation results augmented production function

	Manufacturing (# obs = 1,967)		Services (# obs = 2,381)	
	coeff	se	coeff	se
I) Production function				
Log(capital)	0.212	0.054[1]	0.306	0.070[1]
Log(employment)	0.757	0.341[1]	0.773	0.130[1]
Product innovation (lagged)	–0.135	0.461	0.014	0.176
Process innovation (lagged)	0.263	0.798	–0.024	0.204
Organisational innovation (lagged)	–0.025	0.771	0.293	0.246
E-commerce (lagged)	0.177	0.204	0.658	0.314[2]
II) Evolution productivity states (ω)				
ω (lagged)	0.966	0.009[1]	0.872	0.015[1]
Product innovation (lagged)	0.044	0.007[1]	0.050	0.014[1]
Process innovation (lagged)	0.065	0.007[1]	0.004	0.016
Organisational innovation (lagged)	–0.001	0.006	0.074	0.013[1]
E-commerce (lagged)	0.079	0.006[1]	0.179	0.015[1]

Source: Statistics Netherlands.
Estimations also include year and industry dummies.
[1] Significant at 1%.
[2] Significant at 5%.
[3] Significant at 10%.

Table 5.6.5 presents the results for the (augmented) Cobb-Douglas production for manufacturing and services. The results show 'ballpark' estimates for return to scale with modest scale economies in services (1.08), and slightly decreasing returns to scale in manufacturing (0.97). Interestingly, we found a significant (direct) contribution of e-commerce to value added in services only. The direct contributions of the other types of innovation appear to be insignificant.

[5] A further technical note is that we instrument the innovation dummies in the production function using predictions from the multivariate probit estimated in section 5.2 to take into account their potential endogeneity (see Wooldridge, 2002). The productivity state depends on lagged dummies, which are not instrumented.

The lower panel of table 5.6.5 shows the results for the augmented Markov model. As one would expect, there is a strong persistence in productivity in both branches, witness the coefficient on ω_{t-1} being close to 1, but productivity states depend on innovation and e-commerce too. The impact of e-commerce adoption is strongest, especially in services. Product innovation is important in both sectors, whereas organizational innovation is insignificant in manufacturing, and process innovation in services. So manufacturing firms seem to gain more (in terms of productivity) from optimizing their production process from a technological perspective, while services firms gain more from organizational changes (i.e. new methods for organizing work, and managing knowledge or external relations).

5.6.6 Descriptive statistics for mark-up estimates (augmented production function)

	SBS-IT-innovation panel	
	OLS[1]	ACF[2]
Manufacturing		
number of firms	1,967	1,967
mean	1.324	1.654
median	1.131	1.412
25th percentile	0.932	1.164
75th percentile	1.365	1.705
Services		
number of firms	2,381	2,381
mean	0.916	1.088
median	0.794	0.943
25th percentile	0.608	0.722
75th percentile	1.025	1.217

Source: Statistics Netherlands.
[1] OLS: Ordinary Least Squares.
[2] ACF: Ackerberg-Caves-Frazer GMM estimator.

With the estimates for equation (15), we can calculate new mark-ups, which now account for the effects of innovation and e-commerce. The results are presented in table 5.6.6; recall that we use the translog results for this, so that there is variation in mark-ups over firms and time. The main take-away from this table is that the new mark-ups are on average higher for manufacturing, and lower for services. Consequently, the difference in the degree of competition between the two sectors increases. So taking innovation and e-commerce into account reinforces the finding that competition is fiercer in services. However, again, the decrease in the number of observations, and the associated increase in the average firm size in the estimation sample could also play a role here.

5.7 Summary and conclusions

The adoption and spread of e-commerce may lead to market segmentation with a diverging intensity of competition between segments. In this view, the spread of the internet could increase competition through so-called ‘frictionless markets’ (see Brynjolfsson and

Smith, 2000). This study investigated whether the uptake and spread of e-commerce has affected competition, and vice versa, whether competition matters for the adoption of e-commerce. Using survey data from Statistics Netherlands, our approach complements empirical work in this area, which is mainly based on case studies.

Estimating competition by the profit elasticity measure (Boone, 2008), the general picture is that the level of competition is higher in manufacturing than in the other branches, but somewhat declining. By contrast, competition increased slightly in services, possibly consistent with the fact that the advent of e-commerce has been more pervasive in this sector. Moreover, when we related this measure of competition to the adoption of various innovation types, we found that more competition is associated with a higher probability of adoption of product innovations, but that it negatively affects the probability of engaging in organizational or IT innovation. So stimulating innovation through increasing competition could work for some but not for all types of innovation.

Using the same methodological approach as advocated in the recent export/productivity literature (e.g. De Loecker and Warzinsky, 2012), we estimated firm-level mark-ups and determined the relation between these mark-ups and e-commerce. We found a considerable heterogeneity in mark-ups. So firms are subject to different degrees of competition, even within the same branch. An interesting methodological finding was that accounting for endogeneity of the input factors, leads to higher mark-ups, implying lower levels of competition. So not properly modelling the production function can lead to overestimating competition. In line with the profit elasticity, using the mark-ups, competition is found to be stronger in manufacturing. However, for the smaller samples with linked survey data, we find the converse. The firms in the linked samples are on average larger. Larger firms in manufacturing suffer less from competition than those in services, while smaller firms in manufacturing suffer more than their counterparts in services. In a more general model that includes innovation as a determinant of productivity, we also found that the mark-ups are on average higher for manufacturing, and lower for services, thus reinforcing the finding that competition is fiercer in services. However, this result may be affected by the fact that we had a smaller estimation sample with, on average, larger firms. The impact of selection as a consequence of linking different surveys is an important issue for further research.

Finally, we found a negative relation between mark-ups and e-commerce, implying that an increase in the intensity of e-commerce increases competition. In line with the overall increase of competition and e-commerce activities in services (in particular B2C, business-to-customer), there is evidence that the impact of e-commerce on competition is stronger in services.

6. Dynamics and aggregate productivity: the role of ICT

In this chapter we discuss how we determined the entries and exits in Dutch industries and how we performed a decomposition analysis of industry level labour productivity growth. Reallocation and exit contribute to productivity growth in ICT-intensive industries, whereas in other industries there is evidence of misallocation. Moreover, the crisis was particularly cleansing for ICT-intensive industries: inefficient firms exited the market and resources were allocated to more efficient ones. ICT intensity correlates positively with allocative efficiency, market concentration, dispersion, and turbulence[1].

6.1 Introduction

A good representation of the dynamics that underlie macro-economic developments requires a good look at changes in the population of firms and changes in the allocation of production factors between firms. In a flexible, efficient economy the less productive firms are replaced by more productive ones, and production factors are allocated from the less to the more productive firms. This notion is backed up by an extensive empirical literature about the important role in aggregate productivity of entry, exit, and changes in the relative size of firms (Bartelsman and Doms, 2000, Syverson, 2011).

Since ICT is believed to make firms more flexible in adapting to economic shocks, and also more efficient in their production process, it is an interesting question whether the dynamic process of reallocation, entry and exit, is faster or better in relatively more ICT-intensive than in less ICT-intensive industries. Syverson (2011), for example, stated that the productivity growth in retail trade is primarily due to the substitution of less productive individual stores by larger, more efficient and ICT-intensive chains (with Walmart as the most prominent example).

The impact of ICT can be motivated further by looking at the various roles it may play in the business process (see e.g. Zand, 2010). Firstly, at a basic level, firms that have automated different tasks that used to be done by workers are more flexible in responding to shocks because of lower costs associated with hiring, firing, or hoarding workers. Brynjolfsson et al. (2008) showed evidence of increased turbulence and concentration in ICT-intensive industries because firms can scale up production relatively easily when a certain business model or concept proves successful. In addition, ICT allows firms to gather and share information quickly and to be aware of external and internal developments. For example, enterprise resource planning and supply chain management software allow firms to automatically update information on inventories of customers and suppliers, so that production and the purchase of intermediate goods can be adjusted accordingly. When information systems are linked or integrated between different business processes, all processes can be aligned. ICT also enhances the innovative capacity of firms (Polder et al., 2010a; Spiezia, 2011) so that firms in ICT-intensive industries may be faster in finding new ways of producing, (re-)organizing processes or developing new products in order to cope with changing circumstances.

[1] A revised version of this chapter will appear in the Journal of Technology Transfer.

The specific nature of the digital economy and information goods also bears on the dynamics and distribution of firm performance. Due to the typical combination of high fixed cost and low marginal cost, the distribution of performance measures becomes increasingly skewed (Shapiro and Varian, 1998; Brynjolfsson and MacAfee, 2014). Some markets that are subject to network effects and where externalities play a major role, may even tend to become 'winner-takes-all'. This tendency is further reinforced by the fact that digital goods are non-rival, allowing the market to converge to a single standard. This means that revenues or market shares are being divided over a few firms, while a significant number of competitors are left behind. This way markets become more concentrated, while the spread in performance is increased.

ICT may also affect business dynamics through competition. There is evidence that ICT increases competition due to increased market transparency, lower search cost, increased possibilities of experimentation et cetera (Brynjolfsson and Smith, 2000; see also chapter 5). This way ICT-intensive industries may be more competitive and poorly performing firms will be driven out of the market sooner. Moreover firms have a greater incentive to increase their productivity.

In this chapter, we discuss our empirical analysis of the business dynamics, productivity growth and distributional features of the labour productivity performance of Dutch industries. We investigated whether differences between industries are related to their ICT intensity. First we categorised firms according to whether they were continuing, entering or exiting. This allowed us to relate the degree of entry and exit (i.e. turnover of firms) to ICT intensity. Then we used this categorisation to perform a decomposition analysis that divides aggregate changes of productivity into components related to the dynamics. We used a linked dataset of Business Register data and data from the Production Statistics. This posed some challenges in terms of coverage and calculation of productivity. We explored whether there were differences in the contribution of each of the components that may relate to the degree of ICT intensity. Finally, we calculated various distributional characteristics that describe the spread and turbulence of firm performance, and the efficiency of the allocation of inputs. Again, we explored whether differences between industries could be related to ICT.

Our analysis offers a couple of things which we feel are improvements or new insights. Firstly, our analysis offers an improved identification of entry and exit for the period 2000–2010 for the Netherlands. Secondly, as we used the Business Register for sample weighting in our decomposition analysis, we obtained more representative results for the decomposition of productivity growth than earlier studies. Thirdly, our findings offer new insights in the relationship between business dynamics, productivity and ICT, complementing existing insights in the literature on the role of ICT as a driver of industry productivity growth. Finally, we obtained some interesting results on the differential effect of ICT before and during the crisis.

The setup of this chapter is as follows. We start with a description of the data. Next we describe the continuing, entry and exit classification of firms based on the Business Register (section 6.3), and discuss productivity calculations at the firm-level, as well as our sample weighting method and outlier correction (section 6.4). We describe the bottom-up productivity calculation in section 6.5. Sections 6.6 and 6.7 give the results for the various analyses. Section 6.8 concludes by summarising and pointing out where additional work could head.

6.2 Data

Business Register and Production Statistics

We used the Business Register (BR) at Statistics Netherlands to determine the population of firms. In line with the sampling frame of the Production Statistics we only used firms that were active in December of a particular year. That is, we analysed yearly changes, from December to December. A firm is defined as a unit of economic activity. The BR contains information on a firm's industry, size class, and the number of workers employed. Additional information was available in so-called 'event files'. These files document each registered change to a unit such as a birth, death, merger or acquisition. We used this information to determine whether the fact that we observed a firm for the first/last time in a certain year was due to its actual birth/exit or that something else was the case. This procedure is described below in section 6.3. The Business Register was redesigned in 2006, and many units were reassigned. This made it difficult to analyse entry and exit in the transition from 2005 to 2006. However, even in these years, the event information prevented us from wrongly labelling firms as entry or exit.

The Production Statistics (or Structural Business Statistics) were the source for our productivity analysis. This is an annual survey for a large selection of industries containing information on the outputs and production structure of firms. All firms with more than 20 employees are surveyed, whereas smaller firms are sampled. We used only firms with more than 20 employees in our analysis, because the coverage is too thin to analyse yearly changes for smaller firms. This is a restrictive feature of the productivity analysis, because new firms are likely to start small so their contribution to aggregate growth is likely to be underestimated. Moreover, even for larger firms there may be non-response or other reasons for absence of particular firm in the data. To account for this issue, we used sampling weights, as described in section 6.3.

While all firms in our micro-data are classified according to NACE1.1, we encountered a practical problem for the industry level variables due to the revision of the system of industrial classification in 2008 from NACE1 to NACE2. We needed the user cost of ICT capital (and value added) to construct an ICT intensity measure and deflators for value added and factor inputs to convert nominal into real variables in the productivity calculations. Time series for national accounts variables are not available in the NACE1 classification for more recent years, and the breakdown by type of user costs is only available in NACE2 from the Dutch growth accounts. We therefore used EUKLEMS data, appending NACE1 data up to 2007 to NACE2 data for subsequent years. The appendix describes how we made a consistent time-series for 1996 to 2010, by making use of the double classification in the BR micro-data.

6.3 Preparatory work

Typifying firm dynamics

In this section we describe our typification of firms (units of production) into three categories: Continuing firms (C), New firms (N), eXiting firms (X). A relatively new aspect of our analysis is that we distinguish between 'real' births and deaths of firms from entries and exits due to other events such as mergers, acquisitions, take-overs, or events of a more statistical nature. It is quite common in the empirical literature that entry and exit is measured by comparing the population in two consecutive time-periods. This, however, does not take into account the variety of reasons why production units are introduced or removed from the statistical population. Ultimately, our improved typification will improve insight into the dynamics of industries and its consequences for aggregate productivity changes.

The population of firms was sourced from the Business Register (BR). Information on changes in the population ('events') were used to derive the typification. This information was available in a supplementary file that can be linked to the BR. The following information was available:

- Event action (entering, removal, continuation, correction of a unit)
- Event type (birth, death, mergers et cetera)
- Date of processing.

The event files contain all events for a firm in a particular year. When there are multiple events for one firm, we considered only the first and the last event, as we were ultimately interested in annual changes. A firm can be typified based on its presence in year *t*, combined with its absence or presence in year *t*-1, and the event information. As we used December snapshots of the BR, (not) present in year *t* means (not) present in December of that year.

A continuing firm in year *t* is a firm that is present in the BR in year *t*-1 and in year *t*. We distinguished two types of continuing firms based on the event information. Those without any events are 'true' continuers. If a continuing firm has any events during a year, it is coded as 'continuer with events'; potentially, drastic events may occur that hamper the comparability over time for the latter units. Therefore it is good to be able to distinguish them in a separate category, or leave them out of the analysis.

An entering firm in year *t* is a firm that is not present in year *t*-1 and that is introduced in year *t*. We distinguish two types of new firms:

- a birth
- other (other event types)

An exiting firm in year *t* is a firm that is present in year *t*-1 but not in year *t*. Again, we distinguish two types:

- exit due to death
- other (other event types)

Linking the Business Register to Production Statistics

The next step is to link the Business Register (BR), now including the status (C, N or X) for all firms, to the Production Statistics (PS), from which it is possible to derive the productivity numbers. The match between the two sources is not perfect for several reasons:

- PS are a sample, especially for the smaller firms (size class 40 and lower; 20 employees and less);
- Even for size classes that are surveyed fully, there is the issue of non-response due to non-compliance or mistakes in the sampling frame;
- The attrition due to the above two points is amplified, because we are considering changes in productivity (at least for continuing firms), so that information at the firm-level needs to be available in both the current year and in the previous year;
- PS do not cover all economic activities, so that some industries cannot be part of the analyses.

Although the PS is a stratified sample for firms with 20 employees or less, it was difficult to include these small firms in our analysis. The reason is that the probability of inclusion in the sample decreases significantly due to the need for information on the current and previous year. Moreover, by breaking the figures down by firm status (continuing, entry or exit), the coverage becomes rather thin with a breakdown by industry. Finally, the stratification itself does not take into account the entry/exit behaviour, so that we could not use the standard PS sample weights. In all, we did not think it wise to consider the small firms in our analysis. This was a restriction of our exercise, because young firms (which often start small) may well contribute greatly to the dynamics of an industry. As a consequence the contribution of new firms is likely to be underestimated.

Another thing to note is the occurrence of some rare inconsistencies between the PS and the BR. For example, a firm that is new in year *t* cannot have been included in the PS for year *t*-1. Likewise, a firm that exited in year *t*-1 is not expected to respond to the PS for year *t* (especially as the survey is retrospective and carried out in year *t*+1). Still, such cases existed in the data. This may be caused by the continuous updating of the Business Register with new information on the firm population, so that the Business Register we were using for this analysis may not fully have corresponded to the one that was used for the sampling of the PS. As those cases were rare, they could not influence our end results, so we excluded them from the analysis.

6.4 Firm-level productivity calculations

Labour productivity growth

We calculated labour productivity growth (DLP) based on real value added
$DLP = LP^1 - LP^0$
where 0 is the base period, and 1 is the 'comparison' period, and

$LP^1 = VA^1/L^1$

$LP^0 = VA^0/L^0$

where VA is value added, L is the number of workers, and the superscripts indicate the respective periods. Period 0 value added is in nominal terms, whereas period 1 value added is in prices of year 0. The value added deflator was sourced from the EUKLEMS database as described in the data section. We analysed the absolute rather than the relative change, because it makes the interpretation of the decomposition results easier. However, it is possible to analyse the relative change and proceed in logarithms along the exact same lines. Moreover, our setup allows a straightforward extension to multifactor productivity (MFP) growth, see Polder et al. (2014) for details.

Sample weighting

The sample used for analysis is not equal to the population. By way of example, after all calculations and selections were made, the coverage of our sample in 2007 is as tabulated below.

6.4.1 Sample coverage

Status	Unit	Sample	Population
Continuing (C)	number of firms	12,028	25,145
	% of total	85.96	85.36
Entry (N)	number of firms	1,176	1,789
	% of total	8.4	6.07
Exit (X)	number of firms	789	2,525
	% of total	5.64	8.57
Total		13,993	29,459

Source: Statistics Netherlands.

The percentage below the counts indicates the shares of C, X, and N in the different samples. The relative coverage of continuing firms is similar to that in the population. The share of exits is underestimated, while the share of entry is overestimated. Therefore we made use of a weighting procedure to balance the sample totals to the population.
We opted for a sample-weighting of the results. The observations are categorised by industry, year, size class and status (C, N or X). For each cell we observed the actual population as represented by the number of firms in the Business Register. Also we knew how many firms we observed in the sample used for analysis. To weight our results according to the distribution of firms in the population, we could therefore calculate for each cell the share of firms observed with respect to population, which can be interpreted as an 'ex-post sampling probability'. The sample weight is then the inverse of this ratio.
An issue with weighting is that some cells with observations in the population may have zero observations in the more fine-grained detailed samples. This means that the sample weight cannot be calculated, and that effectively these cells remain empty. Therefore we chose to use an industry classification based on 8 industries (the EUKLEMS industry ALT classification). Moreover, we considered four size classes, 20–50, 50–100, 100–200, and over 200 employees. Together with the breakdown by status (C, N or X), we had no empty cells at these levels of aggregation. Alternative weighting schemes, including those at

a more detailed level, can be investigated whenever feasible. Also there are weighting methods that account implicitly for empty cells (e.g. Renssen and Nieuwenbroek, 1997) that could be further investigated.

Outlier correction

To take care of outliers we used a generic outlier correction, which sets the productivity level of firms in the lower and upper percentile of the productivity distribution to the median value. So we cut off the tails, and rather than throwing the ends away we put them to the value of the middle observation. To avoid artificial changes from year to year, we also put the value in the previous year to the median of the current year, thereby implicitly imposing a zero productivity change for these firms, minimizing their influence on the results.

The advantage of using a generic method of treating outliers is that it is fast and objective. Of course this comes at the cost of perhaps overcorrecting, whereby the variance in the productivity distribution is underestimated. We believe that there is no risk of correcting too little with these data, when using the lower and upper percentiles as a criterion. However, the share of observations being corrected was quite small, and the influence of overcorrecting relatively small compared to the impact of keeping the outliers in the analysis.

Another advantage of putting the observations to the median values rather than throwing them away is that the sample weights do not have to be recalculated. If we had excluded the outliers, the number of observations would change, making it necessary to adjust the weights. So the outlier correction can be turned on and off without consequences for the weighting.

6.5 Bottom-up calculation of productivity growth

For calculating productivity growth by industry we made use of the bottom-up approach, where aggregate productivity growth is a weighted sum of the productivity growth of the underlying units. This approach is discussed at length in Balk (2014). The main issues are how to deal with entry and exit (for which productivity change cannot be calculated), and the choice of weights.

We made use of a familiar decomposition formula from Griliches and Regev (1995). In their approach, aggregate productivity growth is composed of four components. In the formulas below we consider changes from period 0 to period 1, as indicated by the subscripts. The variable P_i refers to the productivity level of firm *i* (either labour productivity, or MFP, or yet another concept); where the subscript *i* is omitted, we refer to the productivity level of the aggregate (hence *P* is the productivity of firm *i*'s industry). Finally, P_i is the share of firm *i* in the total input in a period, e.g. total employment in the case of labour productivity. The

main reason is that this is also the denominator of the productivity term. This ensures that when we calculate productivity growth based on aggregate inputs and outputs, we end up with the same productivity growth as with the bottom approach. That is, it does not matter if we first add up and then calculate aggregate productivity, or first calculate productivity and then take the weighted sum.
The following components are distinguished:

1. productivity change of continuing firms, weighted by average weights (intra-firm or within effect)

$$within = \sum_i ((\theta_{1i} + \theta_{0i})/2)(P_{1i} - P_{0i}) \tag{1}$$

2. average productivity in two periods in deviation from average total productivity, weighted by change in weights (between-firm effect)

$$between = \sum_i (\theta_{1i} - \theta_{0i}) \left(\frac{P_{1i}+P_{0i}}{2} - \frac{P_1+P_0}{2}\right) \tag{2}$$

3. weighted productivity of new firms in t = 1 in deviation from average total productivity in two periods

$$entry = \sum_i \theta_{1i} (P_{1i} - (P_1 + P_0)/2) \tag{3}$$

4. weighted productivity of exiting firms in t = 0 in deviation from average total productivity in two periods

$$exit = \sum_i \theta_{0i} (P_{0i} - (P_1 + P_0)/2) \tag{4}$$

This approach avoids the choice between weights from year t or t-1 by taking the (arithmetic) average of the two.

6.6 Results

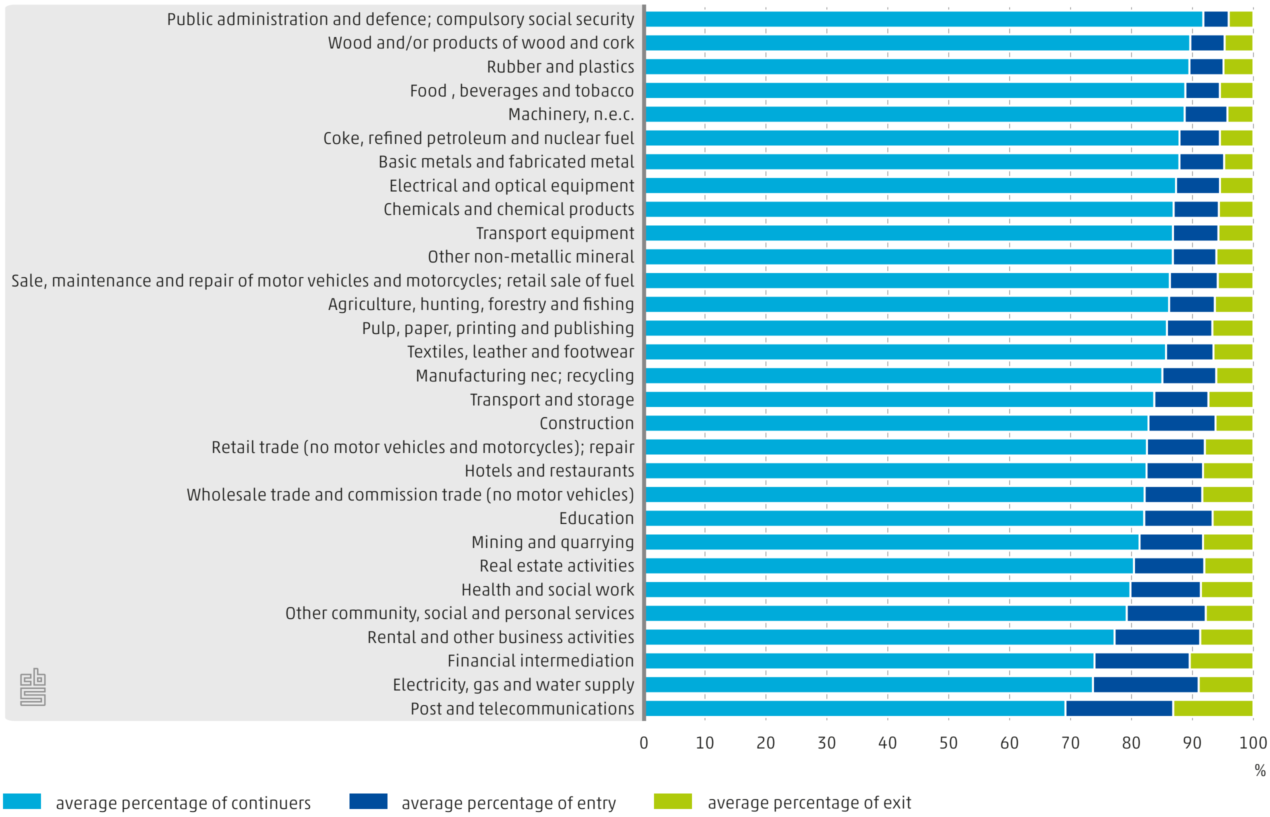
Demography by industry

Figure 6.6.1 shows the results regarding the demography of firms in the way we measured it. The figure shows the average percentage of entry, exit and continuing firms for the period 2000–2010, based on the observations that we typified as true entry, exit and continuing firms (see section 6.3).

The percentage of entry and exit is sometimes referred to as the degree of firm turnover (i.e. number entrants plus exits as a percentage of the total of firms). There is a substantial heterogeneity in this measure of firm dynamics over the various industries, ranging from just over 8 percent in Public administration (L) to over 30 percent in Telecom (64). Another thing to note is that the balance between entry and exit is on average positive, indicating an increasing population of firms, although there is some heterogeneity between industries here as well.

To investigate whether there is a relationship between the ICT intensity of an industry and the degree of entry and exit, we regressed firm turnover on our ICT intensity measure (ICT user cost over value added). The results are reported in table 6.6.2. It turns out that there is a strong correlation between ICT intensity and firm turnover, but once we control for time and industry effects this correlation disappears. So the degree of entry and exit seems not necessarily related to its ICT intensity in the way we measured it, but rather it seems industry specific or related to other industry specific variables.

6.6.1 Average percentage of continuers, entry and exit 2000/2010



6.6.2 Regression of firm turnover (percentage of entry and exit in total) on ICT intensity

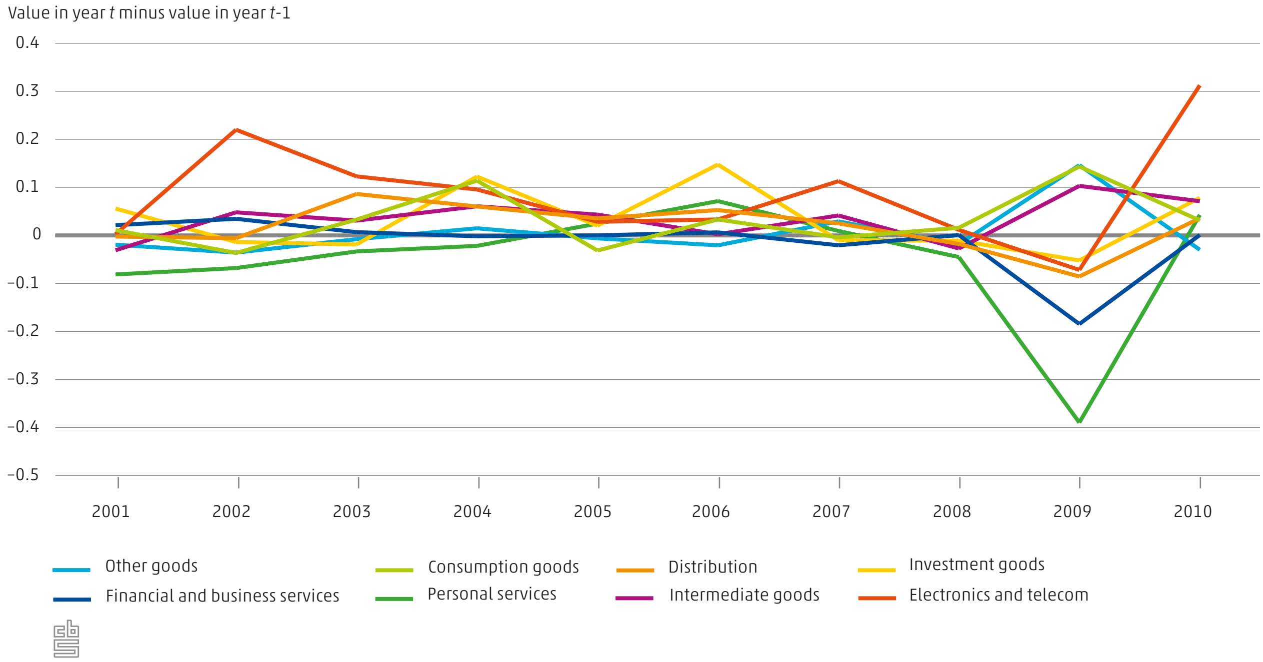
	Coefficient	Robust standard error	Time/industry dummies
ICT intensity	0,699[1)]	0,079	no
ICT intensity	−0,399	0,585	yes

Source: Statistics Netherlands.
[1)] Significant at 1%.

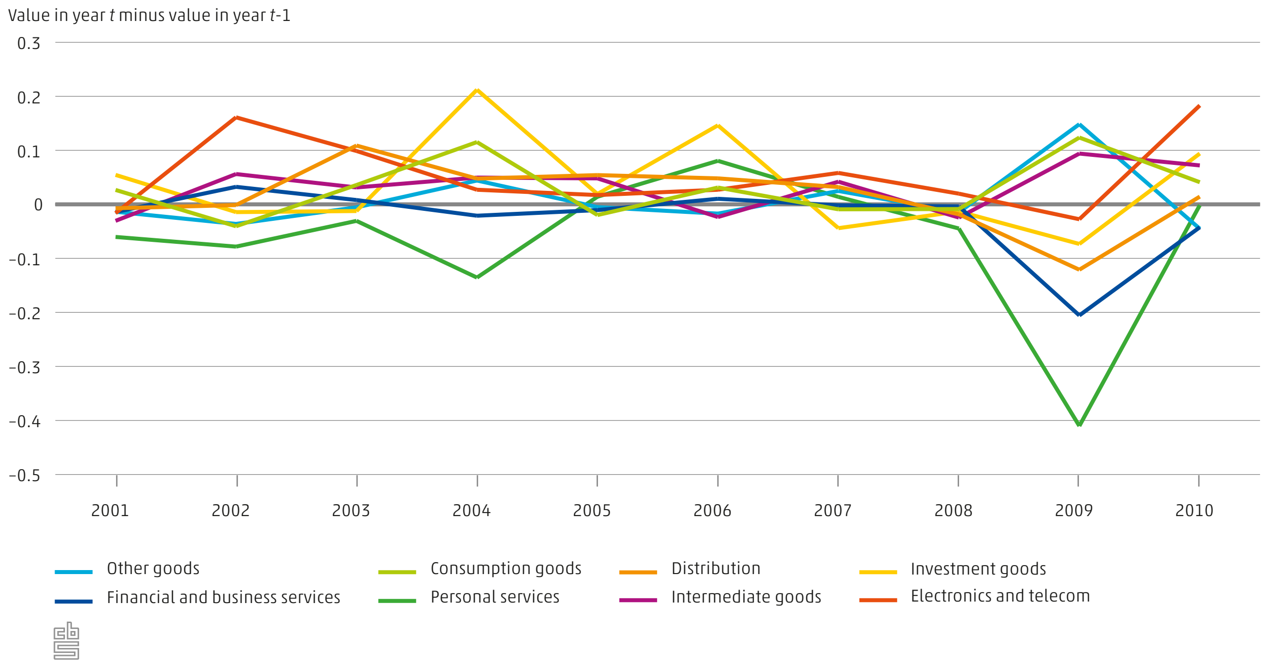
Decomposition of productivity growth

Figure 6.6.3 and 6.6.4 show the results of the bottom-up calculation of annual labour productivity growth, according to the Griliches-Regev method in 8 main sectors according to the EUKLEMS alternative hierarchy (see the EUKLEMS website www.euklems.net for details). These figures are somewhat more volatile than the usual official productivity figures at this level of aggregation. Also there appear to be differences in the patterns by industry between these micro-aggregated figures and the macro ones. For instance, our micro-data show a dip for Finance and Business in 2009. This dip is much less apparent in the macro-data. However, direct comparisons should be made with caution here. Our figures do not include smaller firms, for instance, and exclude observations where the classification of firms as continuing, entry, or exit is dubious. However, judging from figure 6.6.4, including all observations does not change the pattern all that much. Finally, a major difference with the national accounts figures is of course that they result from confronting the production data with a variety of other data sources.

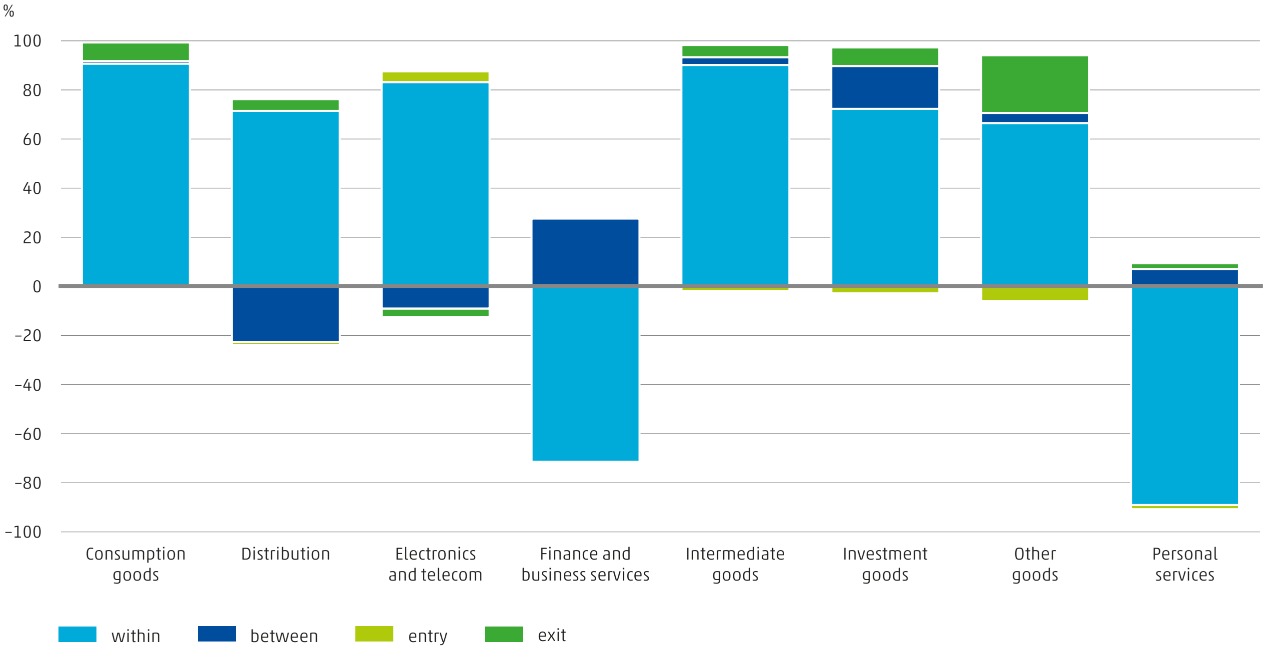
6.6.3 Annual labour productivity growth according to the bottom-up approach



6.6.4 Annual labour productivity growth according to the bottom-up approach (all observations)



6.6.5 Labour productivity growth decomposition, 2000/2010



6.6.6 Labour productivity growth decomposition, 2000/2010, all observations

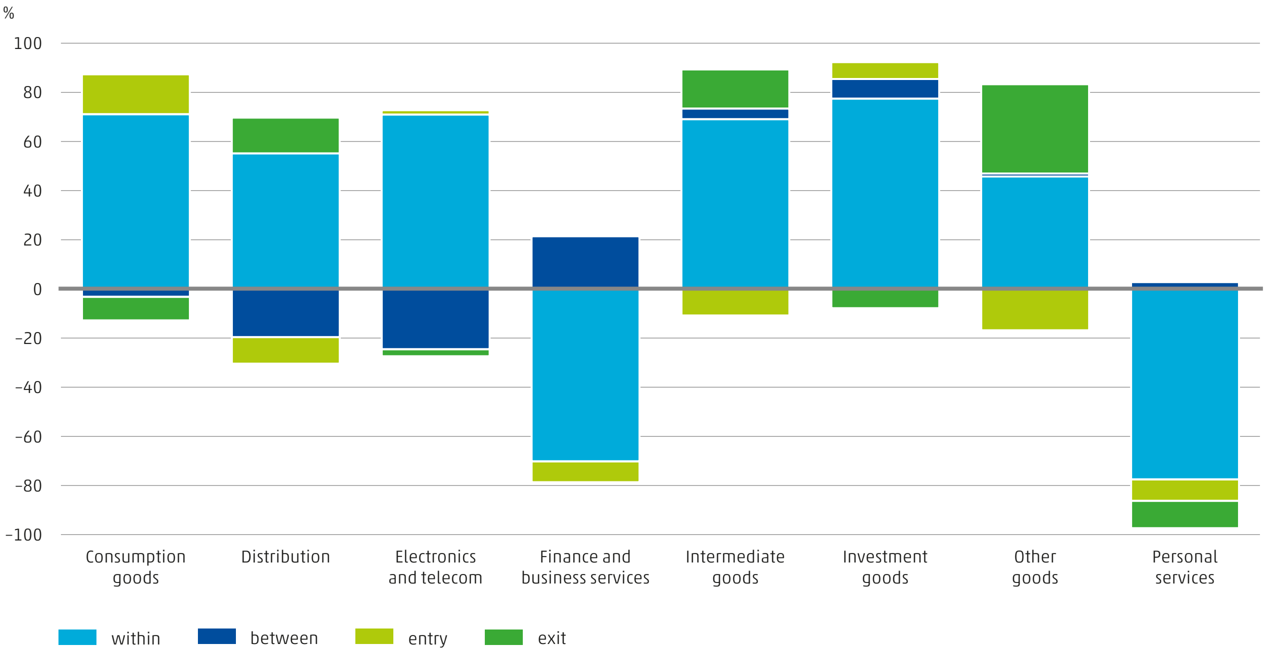


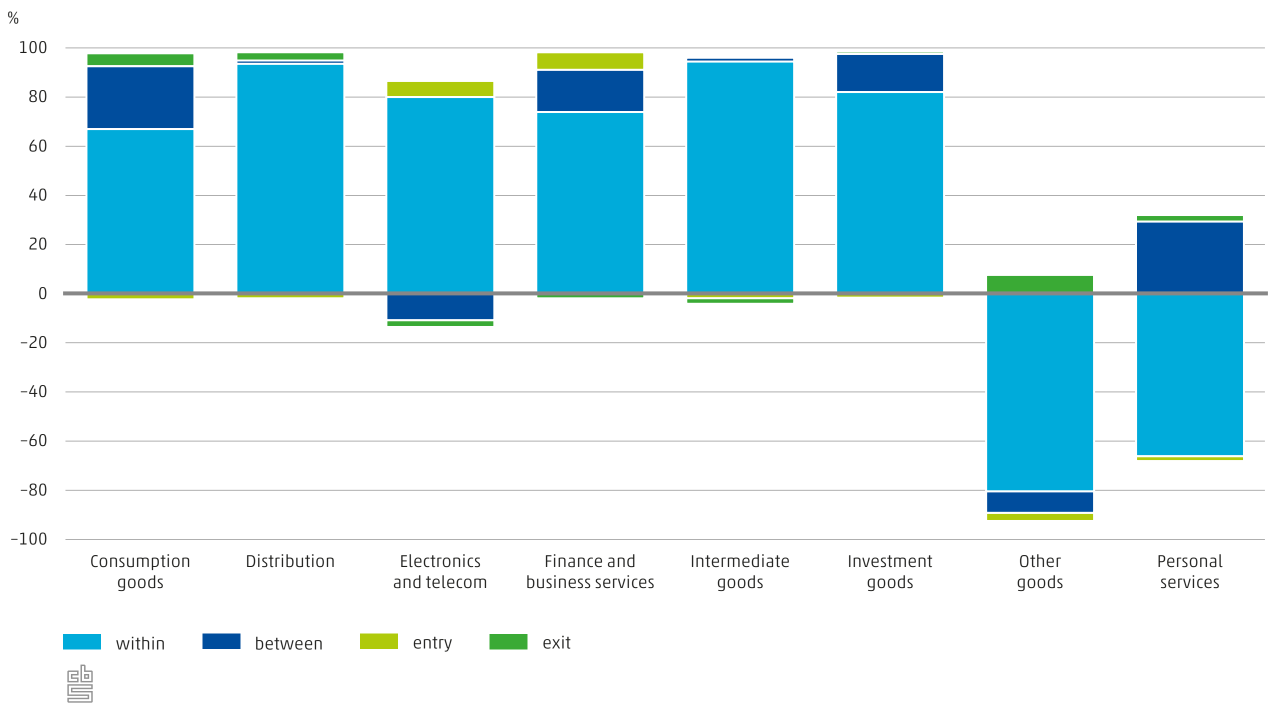
Figure 6.6.5 shows the decomposition of labour productivity changes using only true classifications, based on the weighted figures (i.e. the sample results have been weighted to resemble population totals). The figure presents averages of the different components by year, over the period from 2001–2010.

The results show that there are two industries with a negative growth on average. Also it is clear that intra-firm productivity changes constitute the most important component. This is consistent with earlier findings (see e.g. Balk and Hoogenboom-Spijker, 2003) based on the years before the crisis. However, the between component is non-negligible in most industries, notably in Finance and business services where it counterweighs a negative contribution of the intra-firm changes. The opposite is the case in Distribution: the within component is positive, but the between component is negative. The exit contribution is also visible in most industries, and mostly as a positive component. This means that the productivity of exiting firms is below average, which is desirable with respect to the efficient reallocation of factors production. From these results, the entry contribution is quite low and often negative. It must be emphasised though that due to our focus on larger size classes, it is likely that the entry contribution is underestimated.

Figure 6.6.6 shows the results using all observations regardless of whether the typification is true or fake. It shows that the average growth as well as the size (and even sometimes the direction) of the contribution of the different components can diverge from that based on using the true classifications only. So it is important to interpret the results carefully when there is no opportunity to distinguish true dynamics from those resulting from other reasons.

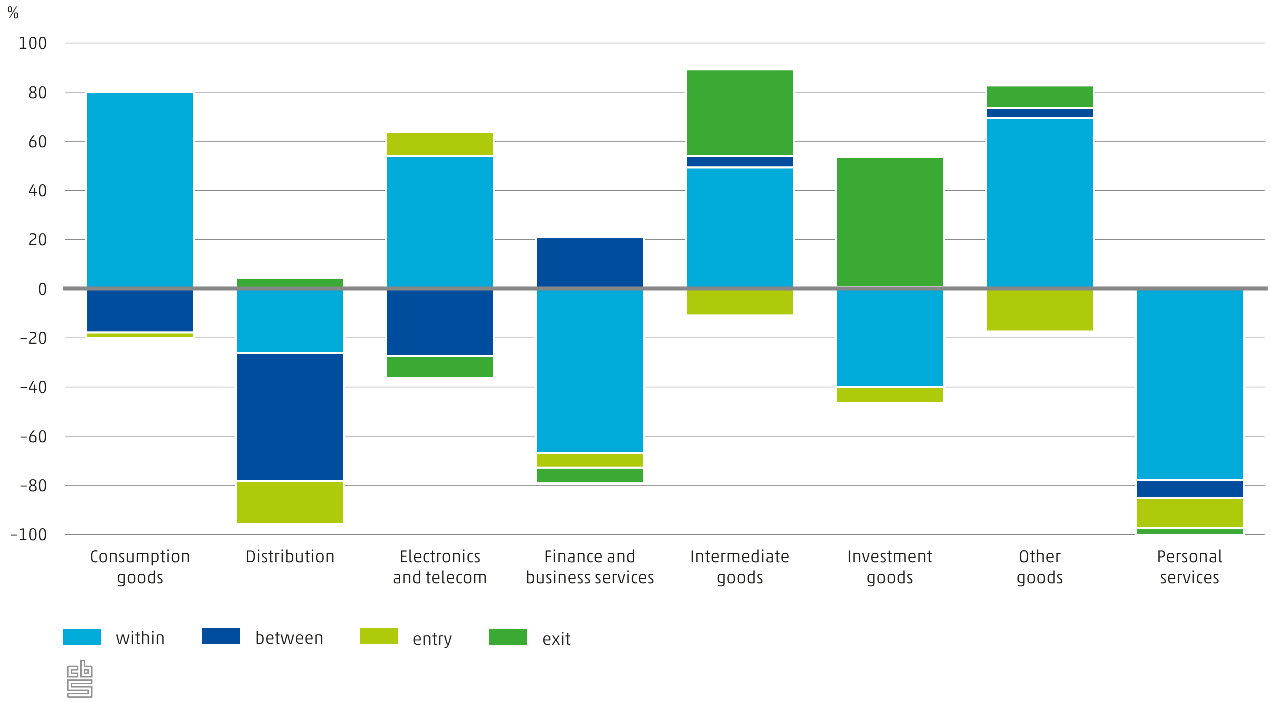
The pre-crisis average and the period 2008–2010 are shown separately in figure 6.6.7 and figure 6.6.8 (only true classifications are included here). Naturally, labour productivity growth is expected to be higher in the former period, but it is striking that only three industries actually show a negative change in the latter. Overall, the exit component becomes more important as one may expect. The fact that it is positive is evidence of a cleansing or 'pruning' effect, in which poorly performing firms are weeded out by the crisis, increasing overall performance. The direction and size of the contributions of the different components vary between the two periods, although the within component

6.6.7 Decompositions by industry, 2000/2007



remains dominant in most cases. Strikingly however, in Distribution we found that the between component has a dominant and negative effect. So the crisis seems to have shifted the allocation of labour to continuing firms that are performing below average in this industry, which is an indication of misallocation. In Manufacturing of investment goods we found that both the between and exit component were more important than the within component in the crisis, but here these components made a positive contribution.

6.6.8 Decompositions by industry, 2008/2010



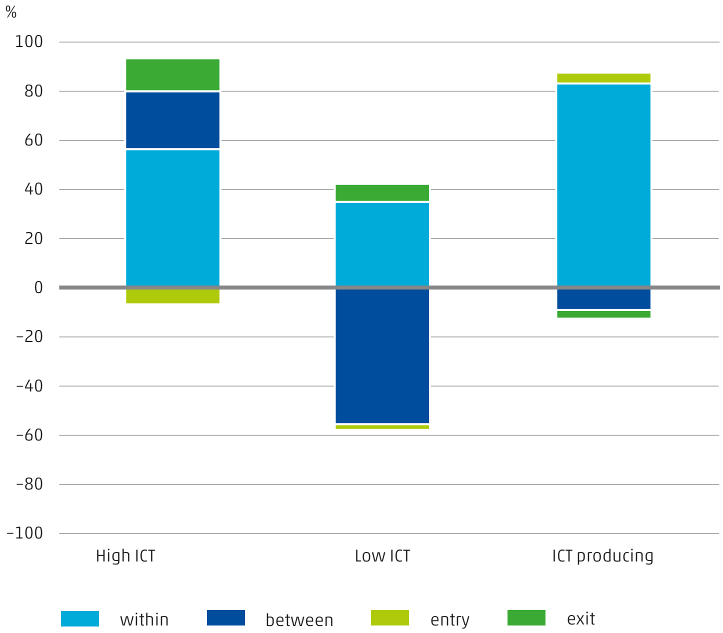
ICT intensity and dynamics of productivity growth

By using a different classification of industries, it is possible to highlight the role of ICT in the dynamics of productivity growth. We follow Stiroh (2002) in defining three types of industries: high ICT intensity, low ICT intensity, and producing ICT goods and/or services. The latter are labelled according to their economic activity (NACE1.1 codes 30 to 33, and 64), while for the first two we made use of the ICT user cost over value added as before, and split the sample into low and high according to whether the mean of this ICT intensity variable is above or below the overall median. We then ran our decomposition procedure again, resulting in figure 6.6.9, which gives the results for all observations or only true classifications.

Firstly, we found that low ICT-intensive industries on average show a decrease in labour productivity growth over the period considered, where high ICT-intensive industries show positive growth, as do the ICT-producing industries. (Note that in construction the results for the ICT producing industries are identical to those for electronics and telecom in figure 6.6.5.) The negative growth in low ICT-intensive industries is mainly caused by a high negative contribution of the between component: this means that resources flow to below average productive firms. If ICT use is related to greater competitive pressure, this result might be interpreted as if a lack of competition is associated with misallocation in low ICT-intensive industries. Although we probably underestimated the entry contribution, the very weak contribution of new firms to overall growth could be a sign that a low degree of competition is reinforced by high entry barriers.

In the ICT-intensive group we found that the within component is dominant, but both the between component and exit contribute positively and significantly to overall growth. So allocation and market selection seem to be more efficient in the ICT-intensive group. Entry has a small negative contribution: entrants in ICT-intensive industries enter at a lower level of productivity on average. In the ICT producing industries, the within component is much more dominant. Entry has a small positive contribution and the between and exit components are slightly negative. Again, a small contribution of entry could be a sign of entry barriers.

6.6.9 Decomposition of labour productivity growth for low ICT intensive, high ICT intensive, and ICT producing industies 2000/2010



6.7 ICT intensity and the distribution of firm performance

As set out in the introduction, ICT affects the development of firm performance and distributional characteristics. Much of an industry's profits may become concentrated among a small number of firms. At the same time there may be a widening gap between the high performance and less well performing firms and the performance of a single firm may become more volatile. Moreover, from an aggregate point of view it is interesting to see whether factor inputs are allocated to the high performance firms. To see whether there is evidence corroborating these phenomena, we looked at correlations between several distribution parameters and the intensity of ICT usage.

Concentration of the market

In the literature, the role of ICT has been described as increasing competition (Brynjolfsson and Smith 2000; and chapter 5 of this volume). This increased competition should lead to lower prices on the one hand, but it can also lead to winner-take-all markets, where the most productive firm takes the largest cut of the pie. Less productive firms see their market-share drop as their market becomes more concentrated. This phenomenon can be measured through a Herfindahl index. The Herfindahl-index is defined as:

$$HERF_{jt} = \sum_{i \in j} msh_{it}^2 \tag{5}$$

where *msh* represents the market share of a firm in overall gross output, persons employed or value added of industry *j*. A market with one single firm has a Herfindahl index of 1, while a Herfindahl index close to 0 means that there is a large number of firms with a low market share. The Herfindahl index is sometimes used as a competition measure: a decreasing Herfindahl index means that the concentration in a market is reduced and, since this is inversely related to competition, this is interpreted as a rise in competition. Boone (2008), however, shows that caution is needed in interpreting the measure in this way. In our case, we use it to assess the concentration in a market only, not for competition per se.

Spread in performance

ICT can make a market more risky, increasing the spread of potential outcomes. To assess this phenomenon, we use two measures here: the standard deviation and interquartile range, denoted respectively as

$$\sigma_{jt}(\log x) = \sigma(\log x_{it}) \tag{6}$$

where firm *i* is in industry *j*, and

$$IQR_{jt}(\log x) = Q_3(\log x_{it}) - Q_1(\log x_{it}) \tag{7}$$

where *x* is gross output, persons employed, labour productivity or value added of firm *i* in year *t*, and Q_1 and Q_3 respectively denote the first and third quartile. The standard deviation takes the whole of the distribution of *x* into account, including the tails and more extreme observations. Because of the potentially high concentration of certain measures, this may be relevant, but it also makes the standard deviation more sensitive for outliers. We used the log of the variables to mitigate this issue. In addition, we also employed the interquartile range, which is the difference between the third and first quartile of the log variable. Because this is the difference between the maximum and minimum value of the middle 50 percent of the observations, outliers are not likely to play a role here. Given the role of concentration in the tails, however, this measure is likely to be a conservative estimate of the actual spread.

Volatility of performance

ICT is also thought to make markets more volatile. For example, ICT-intensive firms may be able to scale up operations more quickly. So the markets with high intensity should have incumbent firms that see their market shares rise and fall faster than less intensive industries. This can be captured by the so-called churn in an industry, defined as the sum of absolute growth in market shares of firms *i* in industry *j*:

$$CHURN_{jt} = \sum_{i\epsilon j}|msh_{it} - msh_{it-1}| \tag{8}$$

Again, we use gross output, persons employed and value added to determine the market shares.

Allocative efficiency

In a similar vein, ICT may play a role in making markets more efficient by distributing resources from relatively uncompetitive firms to the more efficient ones by overcoming frictions more easily. Although resource allocation can incur costs for firms, workers and governments (Andrews and Cingano, 2012), for the most part, shifting resources to the most productive firms boosts aggregate productivity. This allocative efficiency can be captured by using the static cross sectional decomposition developed by Olley and Pakes (1996):

$$P_{jt} = \sum_{i\in j} \theta_{it} P_{it} = \overline{P_{jt}} + \sum_{i\in j}(\theta_{it} - \overline{\theta_{jt}})(P_{it} - \overline{P_{jt}}) \tag{9}$$

where θ_{it} represents relative size in terms of employment, P_{it} is labour productivity of firm *i* in year *t*, and a bar represents simple industry averages.
The decomposition uses the covariance between firm productivity and size. A higher covariance means inputs are allocated more efficiently. This latter term in the decomposition is the so-called allocative efficiency:

$$AE_{jt} = \sum_{i\in j}(\theta_{it} - \overline{\theta_{jt}})(P_{it} - \overline{P_{jt}}) \tag{10}$$

This measure has been used in other empirical work, e.g. Andrews and Cingano (2012) and Bartelsman et al. (2013), to illustrate the relevance of resource allocation for aggregate productivity, and how allocative efficiency is influenced by, for example, the institutional setting in a country.

Relation of distributional characteristics to ICT intensity

We continued to use the ICT user cost as a percentage of value added per industry as an indicator of ICT intensity. To establish a correlation between ICT on the one hand and the four proposed phenomena we estimated the following regressions:

$$\log HERF_{jt} = \alpha + \beta \log ICT_{jt} + d_j + d_t + \varepsilon_{jt} \tag{11}$$

$$\sigma_{jt}(\log x) = \alpha + \beta \log ICT_{jt} + d_j + d_t + \varepsilon_{jt} \tag{12}$$

$$IQR_{jt}(\log x) = \alpha + \beta \log ICT_{jt} + d_j + d_t + \varepsilon_{jt} \tag{13}$$

$$CHURN_{jt} = \alpha + \beta ICT_{jt} + d_j + d_t + \varepsilon_{jt} \tag{14}$$

$$AE_{jt} = \alpha + \beta ICT_{jt} + d_j + d_t + \varepsilon_{jt} \tag{15}$$

All regressions were estimated in both levels and first differences. In the latter case, industry fixed effects were implicitly controlled for the time dimension, and identification of a possible correlation mainly came from those. In the level equations, we controlled for industry and time specific effects by including dummies (*d*) for both effects. Finally, ε is the error term. Because of skewness, we took the log transformation of the Herfindahl index. We also calculated the standard deviation and interquartile range on the log of the concerning variables. In these cases, we also took the log of the ICT intensity variable in the regression. The allocative efficiency parameter can take both negative and positive values, making it unsuitable for a log-transformation. The churn variable is based on shares, and therefore there is no need to use the log transform.

The regression results are shown in table 6.7.1. We show results for the whole data period, and for the period 2000–2007, which excludes the potentially disturbing effects of the crisis. Turning first to the Herfindahl indices there is a positive and significant correlation between the value added measure and ICT in levels. This provides support for the idea that ICT creates winner take all markets. This effect concerns the cross sectional dimension: more ICT-intensive markets show more concentration of value added. But as an industry becomes more ICT intensive, it is not necessarily associated with a higher concentration. We did not find a relationship between concentration and ICT for gross output nor for employment. The correlations became somewhat stronger when we only looked at the pre-crisis period. Possibly the crisis caused firms with low output to exit, thereby increasing concentration if the exit is not matched by subsequent entry of new firms also in less ICT-intensive industries. So in the crisis period, markets may have become more concentrated due to a cleansing effect which occurred independently of its ICT intensity.

The churn variable does not have significant correlations with the level of ICT intensity as it is itself likely to be based on first differences of market shares. However, the growth of ICT is positively related to the churning of markets in gross output and value added. This provides evidence of an increase in turbulence when markets become more ICT intensive, as described by Brynjolfsson et al. (2008). On the other hand, there is no longer evidence of a churning effect when looking at the pre-crisis years. Therefore it seems that the crisis caused additional turbulence in output-based market shares, especially in ICT-intensive industries.

Looking at the regression for the measures of spread, we found evidence that the spread in firm performance in terms of productivity is positively related to ICT intensity in both periods when measured by the interquartile range. This is consistent with early empirical findings by Brynjolfsson and Hitt (2000). However, when looking at the standard deviation, no such correlation can be discerned. Possibly, the standard deviation is subject to outliers in the performance measures which are unrelated to the ICT intensity of an industry. In the pre-crisis period there is also a positive correlation of the spread of value added and ICT intensity, although the standard deviation does not show a significant result for gross output. The fact that including the crisis results in a loss of this significance is consistent with the stronger effects found in the pre-crisis period for the Herfindahl index. Again, if firms at the bottom of the distribution exit due to the crisis, industries become more concentrated and the spread decreases, regardless of the ICT intensity.

It is striking that in all regressions we did not find any evidence between ICT intensity and the spread, churn or concentration of persons employed. The ICT intensity does not seem to affect the distribution of workers, although it does seem to relate to output and performance. A worry is that employment may be inflexible due to hiring and firing cost. If firms cannot hire or shed labour easily, this makes the distribution of labour unresponsive to ICT intensity.

6.7.1 Regression results for distribution measures on ICT intensity

	Method			
	2000–2010		2000–2007	
	level	first differences	level	first differences
Dependent variable				
Herfindahl index of:				
gross output	0.16	−0.02	0.51[3]	0.26
value added	0.75[2]	0.07	1.25[1]	0.20
persons employed	−0.05	−0.63	0.40	0.22
Churn of:				
gross output	0.10	2.10[3]	−0.73	2.23
value added	2.51	3.58[3]	4.17	3.25
persons employed	−1.25	−0.19	−0.44	2.00
Standard deviation of:				
gross output	−0.03	0.09	0.13	0.20
value added	0.07	0.16	0.21[3]	0.20
persons employed	−0.09	0.11	0.01	0.12
labour productivity	0.10	0.07	0.09	−0.01
Interquartile range of:				
gross output	0.16	0.34	0.58[2]	0.45
value added	0.31	0.51	0.66[2]	0.38
persons employed	0.12	0.49	0.28	0.30
labour productivity	0.23[2]	0.24[3]	0.23[1]	0.08
Allocative Efficiency	8.24[1]	3.31	7.64[2]	2.06

Source: Statistics Netherlands.
Year and industry dummies are included in each regression.
1) Significant at 1%.
2) Significant at 5%.
3) Significant at 10%.

Our final regressions took away some of this worry as they show that the allocative efficiency is positively and significantly correlated with ICT intensity in the cross sectional dimension. This supports the idea that resources are allocated more efficiently in ICT-intensive industries. Comparing the two periods even suggests that the crisis mildly boosted allocative efficiency. This can be interpreted as an example of a stronger cleansing effect for the more ICT-intensive industries, because firms with low productivity become smaller or exit, and workers get reallocated to more productive firms. This finding is consistent with our earlier results from the decomposition analysis of more efficient market selection and reallocation in ICT-intensive industries.

Some caveats regarding our results are in order. Firstly, as noted above, the regressions do not establish causal links between ICT intensity and the four different phenomena. They do however provide some hints of the role played by ICT. All significant correlations are in the expected direction, i.e. ICT is positively correlated to concentration, spread, churning and allocative efficiency. Secondly, due to data restrictions, our industry measures concern relatively high aggregates. Therefore some of the industries we label as markets are fairly large, while even smaller NACE classifications may from the perspective of a firm not act as a single market. Although not specific to our study, this is a further caution when interpreting the results.

6.8 Summary of findings and future research

ICT makes firms more flexible and efficient in their production process. This may have consequences for business dynamics and distributional characteristics of firm performance. Using detailed information on entry and exit, we therefore investigated whether the dynamic process of reallocation, entry and exit, is different in ICT-intensive industries than in less-intensive industries. In addition we investigated whether distributional characteristics that describe the spread and turbulence of firm performance and the efficiency of the allocation of inputs are related to ICT.
Following our typification methodology we found a substantial heterogeneity in entry and exit rates by industry, with the rate of firm turnover (entry plus exit rate) ranging from 8 to 30 percent. The degree of business dynamics does not seem to be related to the ICT intensity, once controlling for industry and year fixed effects. Labour productivity growth calculated with the bottom-up approach was found to be quite volatile, especially in the crisis years, even at higher levels of aggregation. The decomposition of productivity growth over the whole period shows that productivity changes within continuing firms (the within component) explains most of the aggregate change. Exit and reallocation are also important, but the size and direction varies by industry. Entry is relatively unimportant, which could be the consequence of entry barriers, but our restriction to firms with 20 employees or more keeps us from putting too much emphasis on this interpretation. Taking into account whether the typification is true or fake matters for the size and sometimes the direction of the components, stressing the need to be cautious about conclusions with respect to dynamics when one does not have this information.

The crisis seems to have had a cleansing effect in most industries, with an eye on the sizable and positive contribution of the exit component. In the Distribution sector, however, there is evidence for misallocation, with a large negative reallocation component. Overall, contrary to the other industries, the average labour productivity growth tends to be negative in the low ICT-intensive industries. Moreover, there is evidence for misallocation in these industries following from the negative reallocation term. A low level of ICT usage can be associated with lower levels of competition (due to less innovation, market transparency etcetera), which may be the cause of this misallocation. In ICT-intensive industries, the within, reallocation, and exit components all contribute positively to overall labour productivity growth, suggesting that market selection and reallocation work better in such industries, increasing their ability to restructure in response to economic shocks.

Our analysis of the distribution of firm performance provides evidence that the concentration of value added is related to ICT, which is consistent with the idea of lower marginal cost of replication and upscaling together with network effects in ICT-intensive industries. As industries become more ICT intensive, the volatility of market shares also increases, in line with the finding that ICT-intensive industries are more responsive to shocks. Such industries also show a higher dispersion of firm performance, consistent with the idea that the differences between winners and losers become larger in competitive ICT-intensive markets. This is true when the dispersion is measured by the interquartile range but not for the standard deviation, however, a measure that might be plagued by outliers. Overall we did not find any effect of ICT intensity on the distributional characteristics of employment, which could point at a high cost of adjustment for labour in response to changes in output. Finally, we found a positive correlation between ICT and the (static) allocative efficiency in the market, that is the covariance of firm size and labour productivity. Moreover, the crisis seems to be associated with a stronger relation of ICT to this efficiency, indicating again a faster or better restructuring in ICT-intensive industries.

There are some dimensions that we have left unexplored. Firstly, it is possible to repeat our analysis for multifactor productivity. Moreover, we can look at longer time differences, which will impact the relative contribution of reallocation, entry and exit. Other decomposition methods can be used as well, particularly the Diewert-Fox method (Diewert and Fox, 2010) that determines the contribution of entry and exit in a better way. Finally, the use of data on smaller firms should improve the assessment of the contribution of entry, and is high on our wish list.

Appendix

Deriving consistent NACE1 based time-series from EUKLEMS

While all firms in our microdata are classified according to NACE1, we encountered a practical problem for the industry level variables due to the change from NACE1 to NACE2 in 2008. In particular, we needed the user cost of ICT capital (and value added) to construct an ICT intensity measure, and deflators for value added and factor inputs to convert nominal into real variables in the productivity calculations. Time series for national accounts variables are not available in the NACE1 classification for more recent years, and the breakdown by type of user costs is only available in NACE2 from the Dutch growth accounts.

To get around this problem we decided to use both the old and new version of the EUKLEMS database (www.euklems.net). This database has information on ICT user cost and allows the derivation of deflators for the relevant variables. The first release has information up to 2007, for aggregates based on NACE1. To be able to use a somewhat longer time-series, including years from the period before the crisis and the recovery period, we also made use of the 'rolling updates', which are based on the NACE2 level. To make the classification consistent, we translated the new aggregates into the old ones for 2008 to 2010. To do so, we made use of the fact that firms are coded twice in these years in our Business Register, once according to NACE1 and once according NACE2. So using a key between the old and new EUKLEMS aggregates and respectively NACE1 and NACE2, we could give each firm an old and a new EUKLEMS industry code. Moreover, we knew the number of workers employed in these firms.

The reclassification procedure can then be illustrated by visualizing it in terms of a matrix. Say we put all NACE1 categories in the rows, and all NACE2 categories in the columns. For each cell of the matrix we know the population count and employment from the BR. For a specific variable, the easiest way to determine NACE1 totals from information on NACE2 totals is to construct (column) weights from the employment figures (or from the number of firms), and distribute the NACE2 totals over the according columns using these weights. The implied row totals are estimates of the NACE1 total for the variable being considered. We did this for value added, capital user cost, and labour cost, both in current prices and constant (year *t*-1) prices. This allowed us to calculate the deflators for these variables.

For ICT user cost, we followed a somewhat more complicated scheme. The problem with the strategy above is that the change of classification sometimes entailed that one (lower level) industry moves from one aggregate to another. If the sub-industries in aggregates that are being redistributed are heterogeneous in the variable of which we wanted to make a time-series, the strategy above may not be optimal. Suppose two industries are together in the new classification. They are approximately equal in size, but the ICT intensity of one is low and for the other very high, resulting in an on average high ICT intensity. The average is all we can observe. Furthermore, suppose the low ICT intensive industry was in another aggregate in the old situations, in which it was relatively large in terms of employment. This industry then got a high weight (based on its size) in the distribution scheme described above and a high ICT intensity (because it comes from an ICT intensive aggregate), resulting in an improperly high ICT intensity for the (old) aggregate in the more recent years. We found that examples like these or similar cases exist, leading to occasional jumps in the industry time series.

The alternative we have used was to first make use of the 2007 information on ICT user cost. Moreover, we went down one level to two-digit NACE1 and NACE2 to account for the heterogeneity at this level, separating the EUKLEMS aggregates based on persons employed. Again, we constructed a matrix with employment weights, and distributed the 2007 ICT user cost from NACE1 two-digit aggregates to NACE2 two-digit aggregates. We then had a matrix with 2007 ICT user cost by NACE1 and NACE2 two-digit combination. Based on this matrix we could determine new weights to distribute the actual 2008 (and further) NACE2 totals over the NACE1 aggregates, which can be aggregated to the level of the EUKLEMS.

Summarizing, instead of using employment in 2008 to make the weights, we first estimated NACE2 level ICT user costs, and used these to determine the weights used to distribute NACE2 based ICT user cost to NACE1. While using employment to distribute, ICT user cost over two digit industries is still not perfect and the two-digit level may still contain heterogeneity in ICT intensity, the resulting time-series look plausible and consistent.

7. ICT and value chains

Within a national or global value chain, ICT has the potential to increase productivity and create networking effects between firms. When examining the role of ICT, firms are often classified by industry in order to measure the intensity of ICT usage. As ICT usage differs between industries and firms, we suggest a classification based on ICT functionality by firm to obtain a more detailed insight into the effects of ICT on a value chain.

7.1 Introduction

Before the industrial revolution a craftsman would make a complete product, starting by gathering the raw materials and ending by its delivery to the customer. Gradually, this production process was allocated to different people who would each complete part of the product. This separation of steps in the production process has led to the development of value chains. As globalization is now playing an important role in the world economy and many production processes are sliced up and divided worldwide, this is turning into a global value chain. A global value chain can be defined as the value added of all activities that are directly and indirectly needed in a production process (Timmer et al., 2014). A global value chain can have either 'snake' or 'spider' type characteristics. In a snake-like global value chain, the production process takes the form of a sequence, where intermediate products are produced and send on to the next part in the value chain. In a spider-like value chain various product parts are produced at the same point in time and come together in one place for the final assembly. This paper follows Timmer et al. (2014) in referring to all internationally fragmented production processes as global value chains.

The common perception is that innovators, entrepreneurs and pioneers receive the economic rewards for their innovations. This is not always the case. Research shows that another party often reaps the benefits of the innovation instead of the creator, e.g. the firms that supply complementary products or services (Dedrick et al., 2009). So it is crucial to have a dominant design, be able to appropriate a substantial amount of revenue or become a core component in other people's innovations. This has stimulated firms to focus on core competencies and outsource activities such as assembly. With this they have created a global production network or value chain. Creating and developing a successful product in a value chain creates value added for all, not just for the lead firm.

ICT is a key facilitator component in the global value chain. In the last decades, the world trade in ICT goods and services has increased very fast, so ICT is now a major source of economic growth (e.g. Polder, 2014, for a recent analysis for the Netherlands). There are three channels through which ICT contributes to economic growth. First, the output and value added created by the ICT sector contributes directly to GDP. Second, the investments by firms and government in ICT equipment contribute to production. The third channel concerns ICT stimulating productivity and efficiency through network or spillover effects. The fact that ICT plays an important role as a facilitator of the global value chain through global production and communication is an example of this latter channel. This effect gets stronger the more an innovation or type of ICT is used by actors in an industry or economy. For example, increasing automation of processes such as inventory evaluation or electronic billing allows enterprises to further optimize their part of the production chain and get more in sync with suppliers and buyers.

Due to the increased worldwide fragmentation of production processes, firms frequently operate in global production or value chains. This development has led to an increase in the trade of intermediate products, intra-industry trade and a growing interdependence between international buyers and sellers (Lemmers et al., 2014). A value chain is the process by which technology is combined with material and labour inputs, after which the processed inputs are assembled, marketed and distributed. A single firm may consist of only one link in this process or it may be extensively vertically integrated (Kogut, 1985). The 'smiling curve' is often cited for value chains in the ICT sector, with value added being higher for the actors at the beginning and end of the value chain than for actors in the middle.

In this chapter, the focus is on the role of ICT in this global value chain. The setup of the chapter is as follows. First, we describe the data used in the analyses and the ICT categorizations. This is followed by an exploratory analysis, which describes different internationalisation characteristics of companies in the different ICT categories. The role of ICT in the global value chain is addressed in the next section. The paper concludes with an extensive factor analysis which suggests a way of classifying companies on the basis of their individual ICT use instead of a classification by NACE code as is traditionally done.

7.2 Data description

A broad dataset was created, which allows insight in ICT and global value chains. Its starting point was the Business Register for the years 2009–2012. To this data we matched additional information from the international trade in goods and services statistics, data on foreign ownership from the Foreign Affiliate Statistics (FATS) and information on ICT usage from the ICT survey and activity in a global value chain (GVC) from the GVC survey.

The Business Register has information available on enterprise characteristics such as the economic activity and size of the enterprise. The economic activity of an enterprise, indicated by its NACE code, is a classification found in the Business Register. Enterprises are clustered according to their intensity of ICT usage and by whether or not they are ICT producing (for specifications, please refer to section 7.3). Based on their size class, we categorised enterprises as small (less than 50 employees), medium-sized (between 50 and 250 employees), or large (250 employees or more).

Locus of control is determined on the basis of the location of the ultimate controlling institute (UCI) of a firm, which is the product of the FATS. In this chapter only two categories of ownership are used, namely Dutch versus foreign controlled. Unfortunately, the sources of the UCI are not comprehensive: if no information is available Dutch ownership is assumed.

The international trade status of a firm is derived from the international trade in goods and services statistics and is grouped in the categories trader and non-trader. Whereas information on all firms was available for the international trade in goods, we only used information for large companies in the international trade in services analyses as this information was integrally available for several years. Apart from this broad dataset for describing company characteristics in general for multiple years, the analyses are completed by using information from the ICT questionnaire and the Global Value Chain and Sourcing questionnaire from the year 2011. These questionnaires are based on a sample of companies. In table 7.2.1, information is compiled about the number of cases available in each of the sources.

7.2.1 Data overview

Source	Nr. of enterprises in sample
Business register	1,300,000 – 1,500,000[1)]
FATS	1,300,000 – 1,500,000[1)]
International Trade in Goods	1,300,000 – 1,500,000[1)]
International Trade in Services	420[2)]
ICT	8,000
Global Value Chain	1,500

Source: Statistics Netherlands.
1) The total number of cases varies because several years of this source are used.
2) As only large companies are used, the number of cases in this sample is constant even though multiple years of the source are used.

7.3 Categorisation of ICT firms

ICT relatedness of a firm can be categorised in several ways. One of the most common categorizations is based on their industrial classification. In our case this is NACE. In this approach the business in which a company is active serves as an indication for the level of ICT use. In this study we followed the approach as suggested by van Ark et al., (2003). Although it is American in origin, it can also be used in the European context (Van Ark et al., 2002). This approach is based on the share of ICT investment and capital in the total investment and capital and divides companies in either 3 or 7 segments. In the three segment approach, companies are divided in ICT-producing firms, ICT-using firms and non-ICT firms. This segmentation can be split up further into seven categories according to whether firms fall into manufacturing, services or other industries. See table 7.3.1.

7.3.1 ICT categories

3 category approach	7 category approach
A. ICT-producing firms	1. ICT-producing manufacturing firms
	2. ICT-producing services firms
B. ICT-using firms	3. ICT-using manufacturing firms
	4. ICT-using services firms
C. Non-ICT firms	5. Non-ICT manufacturing firms
	6. Non-ICT services firms
	7. Non-ICT other industry

Source: Statistics Netherlands.

In the first part of the result section, the ICT firms will be divided according to this NACE approach in order to describe the general characteristics and results of ICT intensity in the different categories. However, structuring the usage of ICT by NACE comes with the risk of generalisation. The nuances in ICT usage can never be captured and the differences between firms are lost. Firms within the same industry may differ in their use of ICT (Polder, 2014). Therefore, the second part of this chapter is devoted to developing a firm-based indicator of ICT usage instead of an industry-based approach. We investigated to what extent the firm-based approach results in different outcomes from the industry-based approach.

General description of ICT categories

ICT-producing firms

ICT-producing firms can be subdivided in ICT-producing manufacturing and ICT-producing services firms and are the smallest category of the three, consisting of a little more than 52 thousand firms. This is less than 4 percent of the entire business population in the Netherlands. This category includes firms in the area of computer, electronic and optical products (manufacturing); and telecommunications and computer programming (services). The sector is dominated by large companies as most employees in this category work for large firms (table 7.3.2). In ICT-producing services, judged by the number of employees, small firms are dominating. But the large firms are also relatively prevalent in this sector.

ICT-using firms

ICT-using firms consist of ICT-using manufacturing and ICT-using services firms. Almost 410 thousand companies are ICT-using firms; this comes down to one in three. Companies in this category are active in the manufacturing of machinery, transportation or electrical equipment or in the wholesale and retail, publishing, financial services, R&D or advertising sector. Employees in this sector work mostly for large or medium-sized firms when in manufacturing, and for small firms in the services sector (table 7.3.2).

Non-ICT firms

The non-ICT firms' category is the largest including over 65 percent (868 thousand) of the business population of the Netherlands. The non-ICT firms can be divided into three categories: non-ICT manufacturing, non-ICT services and non-ICT other companies (e.g. government organizations). It is a very broad category and includes companies that do not use ICT as a core ingredient for competitive advantage in their production or service

7.3.2 Firm size per ICT sector

Percentage of employees per sector and company size	Small firms <50 emp.	Medium-sized firms 51–250 emp.	Large firms >250 emp.
	%		
1. ICT-producing manufacturing	27	29	44
2. ICT-producing services	46	16	38
3. ICT-using manufacturing	28	34	38
4. ICT-using services	53	15	32
5. Non-ICT manufacturing	32	26	42
6. Non-ICT services	31	15	54
7. Non-ICT other industries	64	15	20

Source: Statistics Netherlands.

processes, at least according to their main economic activity. They vary from textile producers to agricultural companies and from education and health care to construction companies. Companies in the non-ICT sector come in all sizes (table 7.3.2), due to the great diversity in their underlying industries. It is precisely because of this great diversity within this group that conclusions about non-ICT firms should be drawn with care.

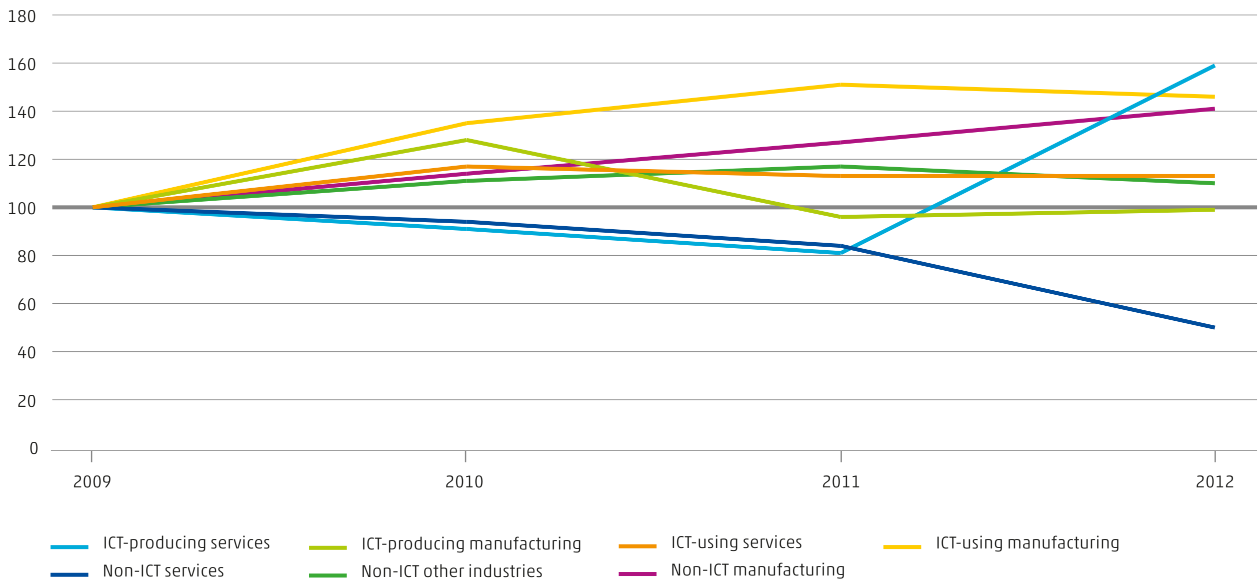
7.4 Exploratory analysis

The purpose of this exploratory part of the chapter is to describe the various ICT categories in their relation to globalisation. We focus on three different internationalisation components, being international trade in goods, international trade in services and foreign investments in the firm (foreign ownership). Companies with internationalisation characteristics are regarded as more successful as they provide more job security, pay higher wages and have a higher productivity per employee (Bruls en Lemmers, 2014; Jaarsma en Lemmens-Dirix, 2010; Fortanier en Korvorst, 2009). The combination of the ICT categories with these internationalisation items allows the description of internationalisation, and therefore the embeddedness in global value chains, of companies in the different ICT categories.

International trade in goods and ICT categories

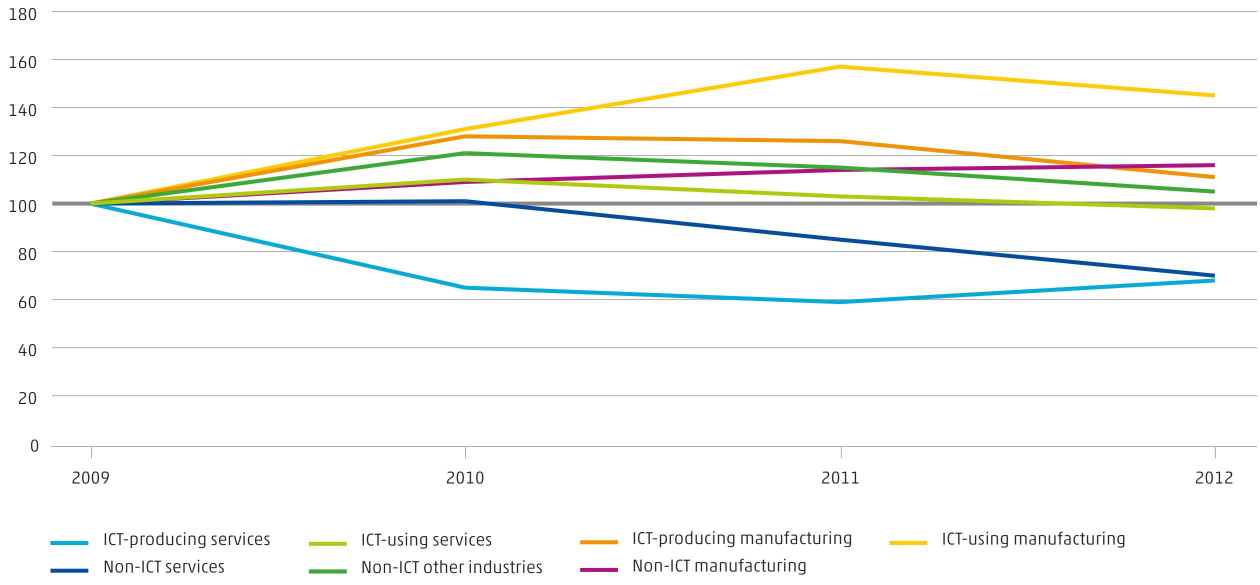
The graphs in figure 7.4.1 and 7.4.2 describe the general development of goods imports and exports in the period 2009–2012. The graphs show a major difference between services and manufacturing firms, which makes the breakdown into seven categories preferable over that into three categories. In addition to this distinction between manufacturing and services, there seem to be different developments between the different ICT categories in the international trade in goods.

7.4.1 Imports of goods (2009=100)



It is interesting to see the development over time in imports and exports. While non-ICT manufacturing firms on average show a steady increase in the value of traded goods, the ICT-producing manufacturing sector showed a major drop in imports and exports in recent years. Among ICT-using manufacturing firms, the international trade in goods increased until 2011 and showed a small dip in 2012. The imports of ICT-producing services companies show a strong increase from 2011 to 2012. But goods imports and exports by the services sector are naturally quite small, so that a relatively small increase in absolute values has much more impact when reported in index values.

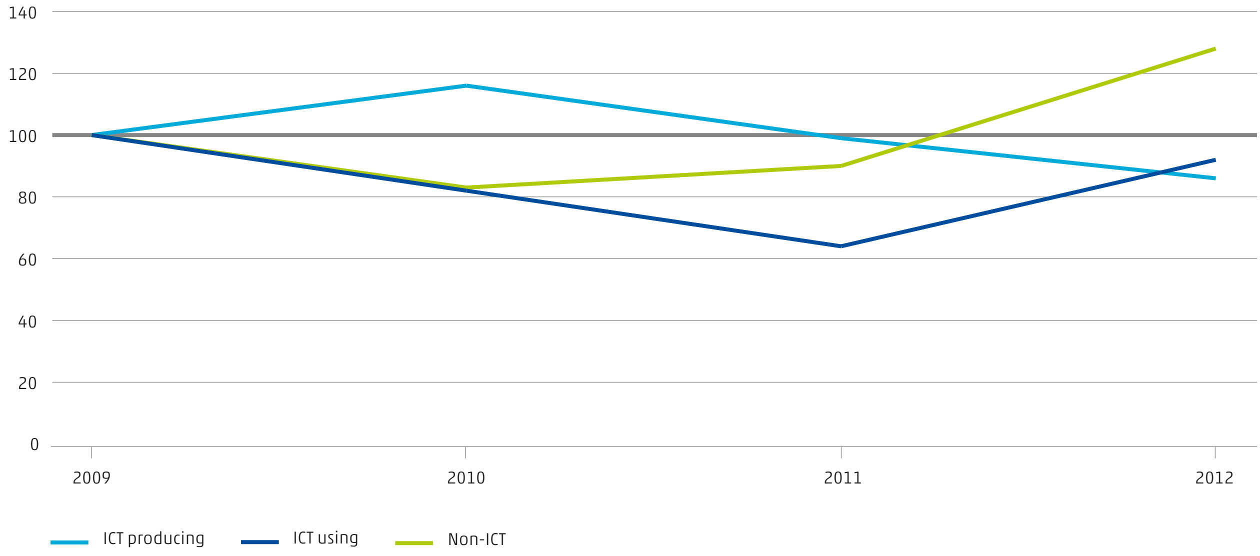
7.4.2 Exports of goods (2009=100)



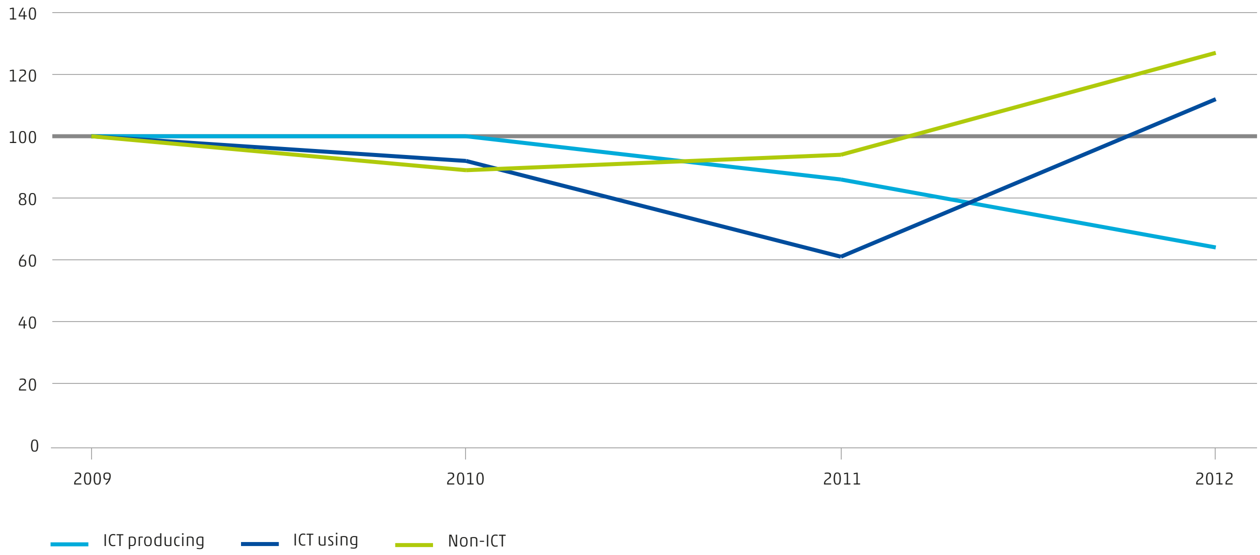
International trade in services and ICT categories

There seems to be a less pronounced difference between manufacturing and the services industry when we look at the micro-data of the international trade in services. This is not surprising as services form an integral part of any business process (Vargo and Lusch, 2004). Due to this and to data related issues, we will not distinguish between manufacturing and services, and will assess the indexed development of imports and exports in services based on the three (rather than seven) categories of ICT-producing, ICT-using and non-ICT companies. Based on this analysis, we see in figure 7.4.3 and figure 7.4.4 that both ICT-using and non-ICT firms show a decrease in their international trade in services until 2011, followed by a recovery. The ICT-producing firms start with a small increase in services trade, followed by a decrease for the following years. This pattern holds for the imports as well as for the exports of services.

7.4.3 Imports of services (2009=100)



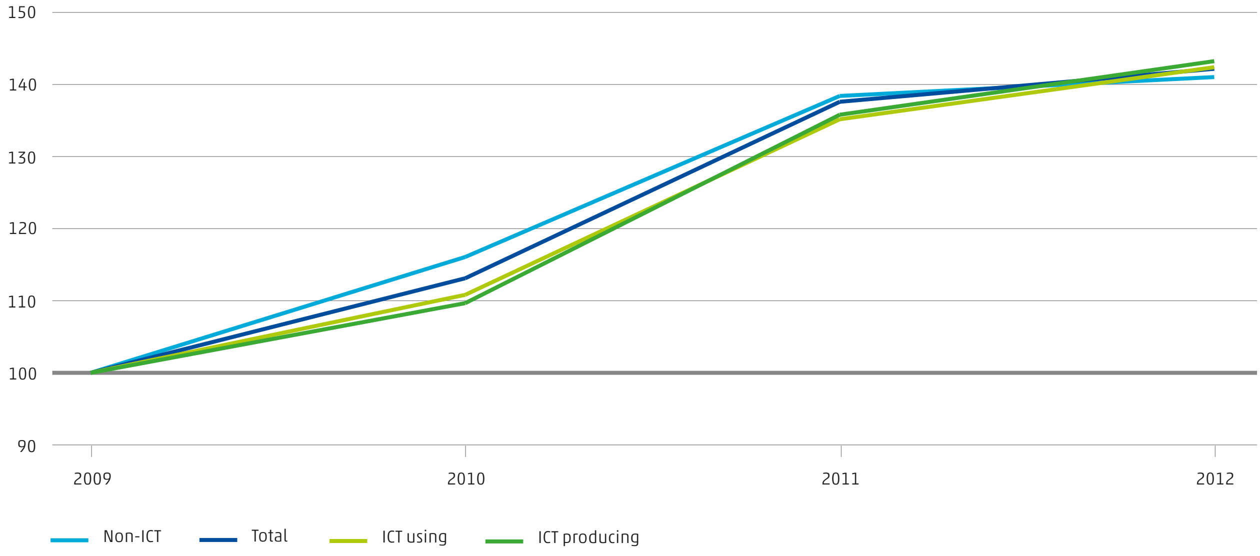
7.4.4 Exports of services (2009=100)



Foreign ownership and ICT categories

Figure 7.4.5 shows that the share of firm in foreign ownership steadily increased among all three ICT categories. This is the only internationalisation characteristic that is hardly impacted by the ICT categories. Both the share of firms in foreign ownership and the growth in this percentage are relatively equal among the three ICT categories.

7.4.5 Foreign ownership (2009=100)



7.5 ICT usage and the global value chain

Clustering and participating in a global value chain is a strategy to enhance enterprise competitiveness in international markets (Giuliani and Pietrobelli, 2005). ICT has played a crucial role in facilitating the fragmentation of production and the rise of global value chains, since it has contributed to the reduction of trade and transportation costs by reducing the cost of services and facilitating online transactions (OECD/WTO/World Bank Group, 2014; Baldwin, 2006). As such, making use of ICT allows firms to exploit new opportunities and address constraints to value chain growth and competitiveness. ICT is at the root of any value chain restructuring. It is used to improve the organization of a firms' communication system (e.g. intranet, email), reduce labour costs or shorten production time. Two groups of ICT are identified; 'generic' ICT such as electronic resource planning (ERP) or supply chain management technologies, and 'specific' ICT such as traceability technologies or performance tracking system (Greenan et al., 2009).

Global value chain and ICT intensity

The data from the global value chain (GVC) questionnaire are valuable but their sample size is limited to larger firms only, as was pointed out in section 7.2. In this part of the chapter, global value chain data are used to shed some light on the international activities of firms in the different ICT categories based on their industrial classification. Because of the sample size, the descriptions below are limited to the three-category approach and the results described are intended to be purely indicative and cannot be generalised to the entire firm population. As the GVC data only contain large firms, the ICT-producing and non-ICT firms are overrepresented in the categories with more large companies. So the results from these specific analyses apply solely to large companies. This also leads to the premise that they are more often part of a company group and more often are owned by a foreign company (more than 80 percent) than firms in the ICT-using (more than 70 percent) and non-ICT (more than 60 percent) sectors.

In the GVC questionnaire, companies indicated whether any business functions were mainly conducted abroad. Companies were asked to distinguish between their main business and the support functions of ICT, R&D, Distribution, Marketing and Administration. Having activities abroad indicates that the execution and specialisation of company functions take place in another country than the Netherlands. The activities can be conducted in either a foreign subsidiary or in a foreign external company by means of outsourcing. First, we looked at the total number of activities conducted abroad (see also table 7.5.1). The ICT-producing and ICT-using firms make more use of activities in other countries than non-ICT firms. This difference is statistically significant (with a p-value of 0.02). In total, almost 30 percent of the firms have activities abroad. When zooming in on the specific execution of ICT activities abroad, this goes down to 7 percent. The share of firms with ICT activities abroad is higher among ICT-producing firms than among ICT-using and non-ICT firms. This difference is marginally significant (with a p-value of 0.05).
When firms have activities abroad, these activities differ among the three ICT groups. Where there are ICT-related international activities in almost half of the cases of ICT-producing firms, this goes down to 1 in 4 of the non-ICT firms or even 1 in 5 of the ICT-using firms.

Table 7.5.1 Firms with activities abroad

	Total activities abroad	ICT activities abroad	ICT-activities abroad/ Total activities abroad
	%		
A. ICT-producing firms	34	14	42
B. ICT-using firms	35	7	20
C. Non-ICT firms	27	7	24
Total	29	7	24

Source: Statistics Netherlands.

These results show that ICT-using and ICT-producing firms tend to make use of international business functions to the same extent. However, the role of ICT in the global value chain is stronger for ICT-producing firms, as they use international subsidiaries or daughter companies more often for their ICT activities, while ICT-using firms tend to focus on other activities when engaging in global sourcing. ICT-producing firms also internationalised most activities in the period 2009–2011. They reported three times as often that they moved a business function abroad in the years 2009–2011. Interestingly, most companies in all three categories of the ICT sector report no change in ICT-employees in the period 2009–2011.

7.6 ICT use by Dutch firms in the value chain

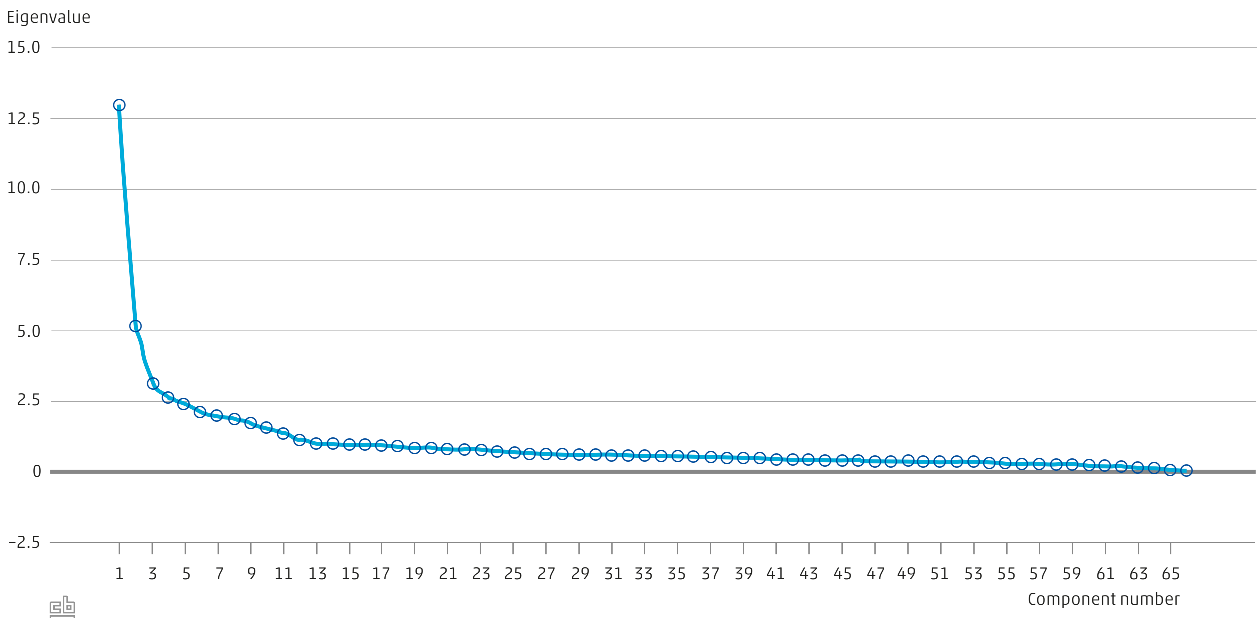
Until this point in this chapter, the ICT use of Dutch firms was based on an average intensity of ICT in their according industries. However, it is quite possible that companies within the same branch make use of ICT resources in a different way and to a different extent. Although agriculture falls into the non-ICT category, much practical advice and empirical evidence can be found on the role of ICT in the agriculture value chain. For instance, ICT plays a major role in agricultural value chains (see e.g. E-agriculture.org), ranging from increased use of mobile phones to expanding networks. Internet access is becoming easier and cheaper to use in daily business. ICT and devices are converging in tasks and performance, offering more flexibility in doing business while becoming cheaper, more user-friendly and energy efficient.

Merely using an industrial classification to describe ICT use in value chains may not suffice. In order to overcome the issues with the industrial classification approach, we also assess the link between firm-level ICT usage and internationalisation. For this purpose we used the ICT questionnaire of the year 2011.

Factor analysis

The ICT questionnaire asks around 8,000 companies for their ICT usage in different contexts. Many of the questions are posed in a format that permits a ‘yes’ or ‘no’ answer, resulting in a total of 59 binary indicators. In order to determine the kind of ICT usage as well as the extent of ICT usage we conducted a factor analysis with these variables from the ICT questionnaire of 2011. Based on an observational judgement categorization, one would

7.6.1 Scree plot



expect to divide the dummies in around four categories. In order to see if this claim also fits the data, an exploratory factor analysis with Varimax rotation was conducted in which the number of factors is based on an Eigenvalue larger than 1 (see e.g. Pallant, 2010, for technical details). This analysis results in 14 factors with Eigenvalues over 1. Scrutinizing the Scree plot (figure 7.6.1) with this analysis, on the other hand, shows an 'elbow' around the fourth of fifth factor.

For the purpose of the analyses in this context, we felt 14 factors were too much to still be meaningful. The analysis resulted in several very small factors which still seemed to be interrelated. Therefore, based on the observational approach and the scree plot, we ran confirmatory factor analyses with four factors and five factors respectively. The four factor solution resulted in one big block of almost 30 items for one factor. In the five factor solution, this block was divided in two separate blocks of variables, each of which can be interpreted as describing a different aspect of value chain integration by means of ICT. Since this closely matches the research topic of this chapter, we decided to maintain a five factor solution. The full output of the factor analysis is available on request.

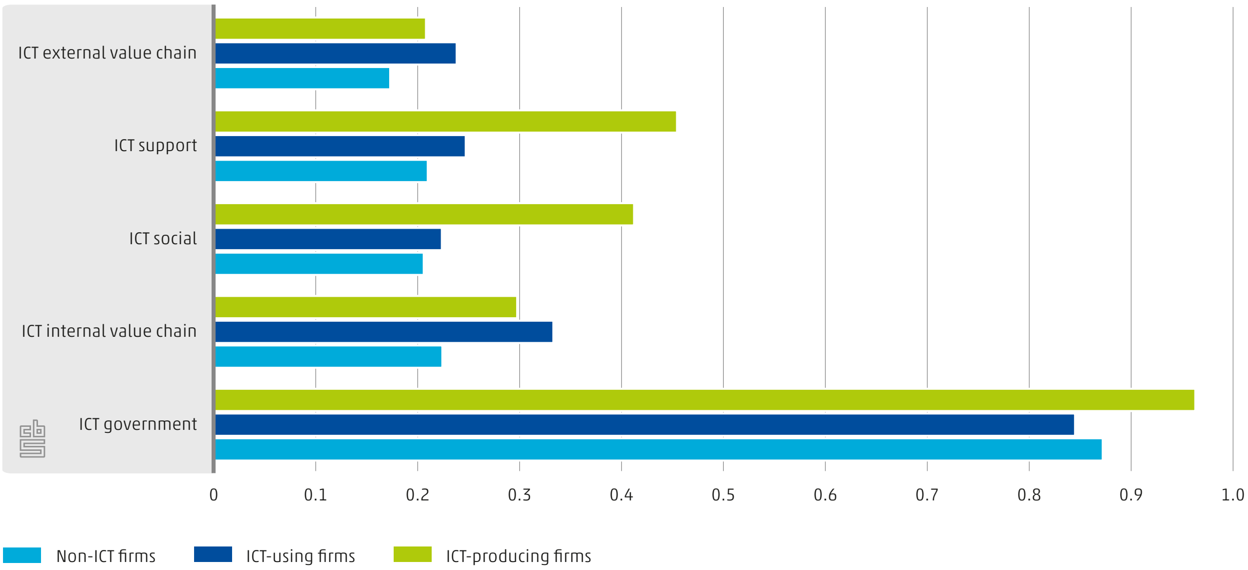
The factor analysis procedure we applied ultimately resulted in five factors which can be described as follows:
1. ICT usage for external value chain integration (ICT external value chain, 14 items): use of ICT for communication and value chain integration with suppliers and buyers;
2. ICT usage for business support and innovation (ICT support, 15 items): use of ICT training for employees, use of ICT devices by employees and importance of ICT in the innovation process;
3. ICT usage for social networking (ICT social, 12 items): use of social media as support for marketing, sales or other business processes;
4. ICT usage for internal value chain integration (ICT internal value chain, 13 items): iCT usage on the company website and as a facility to integrate the different departments in the company;
5. ICT usage for government purposes (ICT government, 5 items): usage of ICT for interactions with the government in the form of taxes, subsidies, assignments etc.

These factors each include a number of binary variables or 'dummies'. Factor scores were computed at the firm level by dividing the number of 'active dummies' by the total number of dummies in that category, resulting in a factor score between 0 and 1. Each company then has a factor score for each of the 5 factors that were determined above. These factor scores are used in the analyses below. For the current study, factor 1 (ICT usage for the external value chain) is the most interesting factor as it describes the use of ICT for the external value chain of a company.

Description of factors in ICT categories

The first step in the analysis is the combination of the factor scores with the ICT categories that were used in the previous analyses. An Analysis of Variance (ANOVA) was conducted in order to see whether the factor scores differed among the NACE-based ICT categories. The ANOVA scores are highly significant for all factors when tested on 3 as well as on 7 categories of NACE-ICT.

7.6.2 Factor scores



The results of this analysis as depicted in figure 7.6.2 show that ICT-using firms make most use of ICT for the integration with the value chain both the external and the internal. The ICT-using services firms are even more strongly focussed on this kind of ICT usage than the ICT-using manufacturing firms. The non-ICT firms have the lowest score on external and internal value chain integration by means of ICT. The ICT-producing firms score highest on the other three ICT-related factors. With ICT support, the ICT-producing manufacturing firms are mainly responsible for the high score while in ICT social and ICT government, the ICT producing services firms score highest. Also in these three factors the non-ICT firms score lowest on the factors.
This implies that when looking at the role of ICT in the global value chain, ICT-using firms are the focal sector as they make most use of ICT for their internal as well as their external value chain. In the next analyses, we will further assess the impact of this ICT usage on company performance and internationalisation. With this analysis, we scrutinized the extent of different ICT usage by different firms.

Regression analysis: relationship of ICT usage to business performance

The computed factor scores can be used in a regression in order to explore the relation of each kind of ICT usage with firm performance and other business related factors.
In order to determine the impact of the ICT usage on business performance the following equation was estimated:

$$\ln(turnover) = \alpha + \sum_{i=1}^{5} \beta_i ICT_i + \beta_6 ITG + \beta_7 ITS + \beta_8 UCI + \beta_9 \ln(WP) + \varepsilon \quad (1)$$

To account for skewness, we use a log linear specification. Turnover is used to measure firm performance, and we control for firm size by including the number of employees (WP, sourced from the ICT survey). The factor scores determined in the previous paragraph are included in the equation as variables ICT1–5. In addition, the internationalisation factors – international trade in goods (ITG), international trade in services (ITS) and foreign ownership (UCI) – are also included as dummy variables in the equation. Finally, ε is the error term.

First, we conducted a regression with all the firms in the sample. The results of this regression are given in the first column of table 7.6.3. The (adjusted) coefficient of variation (R-square) is 0.514 which indicates that more than half of the variance in the data is explained by this model. To interpret the results of this model, we focused on the standardised coefficients and the significance thereof. As the factor scores were not weighted for each individual item in them, it would not be meaningful to interpret the unstandardised magnitude of the effects on turnover. However, by looking at the standardised coefficients and its significance one can say which factor is most strongly associated with the turnover of a company. The coefficients of the internationalisation factors (UCI, ITG and ITS) on turnover can be interpreted directly. These results are shown in the second column.

The turnover of a firm that is involved in the international goods trade is 3 times as high as for firms that are not involved in the goods trade. The other internationalisation factors also show significant results. Use of ICT for the internal value chain is by far the most important factor. The other factors show smaller coefficients and partly have lower significance levels. In this model, however, there is no correction for industry-specific effects. This correction can be done by industry dummies in the model, but as we are not looking at the exact effects of the ICT factors on turnover, but merely at the relative importance of the factors, it is deemed sufficient to run the model for subsamples of the ICT categories (which are based on NACE and are therefore a correction for NACE). This means that the model is estimated three times; once for the ICT-producing firms, once for the ICT-using firms and once for the non-ICT firms.

Interestingly, there is a big difference in results for these three groups. While ICT usage for the internal value chain is important for all firms, the ICT use for the integration of the external value chain only has an impact on turnover in the category of ICT using firms, and the other categories show no significant effect. ICT support on the other hand only shows a significant (negative) effect for ICT-producing firms. ICT use for social media does not have a significant effect on turnover in the case of ICT-producing firms, but it has a negative effect on turnover in the case of ICT-using firms and non-ICT firms. ICT use for the internal value chain is relatively the most important ICT factor for companies in all three sectors. ICT use for government purposes is only significant in case of the non-ICT group. It should be noted that these relationships are not necessarily causal. We will come back to this point below.

The dummy for foreign ownership is significant for all three categories but it is most important in the group of ICT-producing firms. For the ICT users, the international trade in goods is most important as well as for the non-ICT firms.

We note that the adjusted R-square for the model is lowest in the group on non-ICT firms. This may be because this group is a collection of heterogeneous industries. When re-estimating the model with a control for NACE codes in the form of branch dummies, the adjusted R-square shoots up to a level of 0.77.
In all, these results show that firm level indicators contribute to predicting firm performance to a varying extent. Moreover, there are significant differences between industries in the relationship between performance and ICT at the firm level.

Table 7.6.3 Regression results

	Total sample		ICT-producing firms		ICT-using firms		Non-ICT firms	
	standardised coefficient	effect on turnover[1]	standardised coefficient	effect on turnover[1]	standardised coefficient	effect on turnover[1]	standardised coefficient	effect on turnover[1]
ICT external value chain	0.02[4]		0.01		0.05[2]		−0.02	
ICT support	−0.02[3]		−0.04[4]		−0.01		−0.01	
ICT social	−0.05[2]		−0.02		−0.08[2]		−0.03[3]	
ICT international value chain	0.17[2]		0.08[2]		0.10[2]		0.14[2]	
ICT government	0.05[2]		0.01		−0.01		0.09[2]	
foreign owned	0.11[2]	1.71	0.06[3]	1.21	0.03[3]	1.11	0.12[2]	1.94
international trade in goods	0.30[2]	3.04	0.03[4]	1.11	0.08[2]	1.39	0.32[2]	3.26
international trade in services	0.10[2]	1.81	0.02	1.08	−0.03[3]	0.86	0.15[2]	2.51
employment	0.42[2]		0.87[2]		0.83[2]		0.33[2]	
adjusted R-square	0.51		0.86		0.81		0.46	

Dependent variable is log turnover.
Source: Statistics Netherlands.
[1] Effects are calculated with unstandardised coefficients.
[2] Significant at 1%.
[3] Significant at 5%.
[4] Significant at 10%.

It is necessary to emphasise that the relationship between the factors and the turnover does not necessarily describe a cause and effect relationship. A firm with more ICT for the internal value chain might very well have a larger turnover. However, these analyses do not indicate whether this firm uses more ICT in the internal infrastructure because it is larger or whether more use of ICT for the internal infrastructure made it larger. The results on the other hand do indicate a correlation between the use of ICT for different kinds of purposes and firm performance.

7.7 Conclusion

This chapter analyses the role of ICT in global value chains, using different approaches and data. In the first exploratory analyses, ICT-producing firms stood out as firms with most growth and most activities abroad in the field of ICT. However, the method we used – which was purely based on NACE classifications – has some drawbacks, in particular ignoring possible variation in the usage of ICT at the firm level. In search of an alternative approach to measuring ICT in global value chains, ICT usage at the firm level was investigated by means of a factor analysis and regression approach. The results of the analyses show that although firms in ICT-producing industries have more international ICT characteristics, the use of ICT for the external value chain – or the integration with buyers and suppliers – is highest among ICT-using firms. These also show the strongest correlation between their ICT usage for the external value chain and turnover.

Our results indicate that while the type of economic activity matters, it cannot describe the full spectrum of the role of ICT in value chains. When combined with firm-specific characteristics, the role of ICT in a global value chain can be explained more accurately.

Appendix

Table 7.A.1 NACE classification

Description	NACE	ICT 3 digit	ICT 7 digit
ICT producing manufacturing		1	1
Office and company equipment	30		
Fiber optics	313		
Semiconductors	321		
Communications equipment	322		
Radio and TV equipment	323		
Instruments	331		
ICT producing services			2
Telecommunications	64		
Computer services	72		
ICT using manufacturing		2	3
Apparel	18		
Printing & publishing	22		
Machinery	29		
Electrical machinery	31-31.3		
Watches & instruments	33-33.1		
Ships	35.1		
Aircrafts	35.3		
Railroad & other	35.2+35.9		
Other manufacturing	36-37		
ICT using services			4
Wholesale trade	51		
Retail trade	52		
Banks	65		
Insurance	66		
Securities trade	67		
Renting of machinery	71		
R&D	73		
Professional services	74.1-74.3		
Non-ICT manufacturing		3	5
Food products	15-16		
Textiles	17		
Leather	19		
Wood products	20		
Paper products	21		
Petroleum & coke	23		
Chemicals	24		
Rubber & plastics	25		
Stone, clay & glass	26		
Basic metals	27		
Fabricated metal products	28		
Motor vehicles	34		
Non-ICT services			6
Repairs	50		
Hotels & restaurants	55		
Transportation	60-63		
Real estate	70		
Other business services	74.9		
Government	75		
Education	80		
Health	85		
Personal & social services	90-93		
Non-ICT other industries			7
Agriculture	01-05		
Mining	10-14		
Utilities	40-41		
Construction	45		

Source: Van Ark et al. (2003).

Abbreviations

ACF	Ackerberg, Caves, Frazer
ALT	EUKLEMS industry ALT classification
ANOVA	Analysis of Variance
B2B	Business-to-business
B2C	Business-to-customer
BR	Business Register (Statistics Netherlands)
CDM	Crépon, Duguet and Mairesse
CHS	Corrado, Hulten and Sichel
CPA	Statistical Classification of Products by Activity in the European Economic Community
CRM	Customer Relationship Management
DLP	Labour Productivity Growth
DPD	Dynamic Panel Data
DTF	Distance To Frontier
EC	E-commerce survey (conducted by Statistics Netherlands)
ERP	Enterprise Resource Planning
ESA	European System of National and Regional Accounts
EU	European Union
EUKLEMS	Productivity database on EU member states
FATS	Foreign Affiliate Statistics
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GVC	Global Value Chain and Sourcing Survey
ICT	Information and Communications Technology
ID	Identification
IE	ICT Expenditure Survey (conducted by Statistics Netherlands)
IT	Information Technology
ITG	International Trade in Goods
ITS	International Trade in Services
KLEMS	Capital (K), Labour (L), Energy (E), Materials (M) and Services (S)
LAN	Local Area Network
LMR	Labour Market Regulation
LSDV	Least Squares Dummy Variable
LSE	London School of Economics
MFP	Multi-factor Productivity
NACE	Nomenclature statistique des Activités économiques dans la Communauté Européenne
NEC	Not elsewhere classified
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PC	Personal computer
PE	Profit Elasticity
PIM	Perpetual Inventory Method
PMR	Product Market regulation
PS	Production Statistics (compiled by Statistics Netherlands)
R&D	Research and Development
SBS	Structural Business Statistics
SCM	Supply Chain Management

SN	Statistics Netherlands
SNA	System of National accounts (United Nations)
SSB	Sociaal Statistisch Bestand (Statistics Netherlands' social statistical file)
SW	Software
SYS-GMM	System Generalized Method of Moments
TFP	Total Factor Productivity
UCI	Ultimate Controlling Institute (Dutch or Foreign ownership of an enterprise)
UK	United Kingdom
USA	United States of America
UWV	Uitvoeringsinstituut Werknemersverzekeringen (Dutch labour exchange)
VA	Value added
WIFI	Technology for Wireless Internet
WIOD	World Input Output Database
WTO	World Trade Organisation

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