INNOVATION AND PERFORMANCE

A COLLECTION OF MICRODATA STUDIES

INNOVATION AND PERFORMANCE

A COLLECTION OF MICRODATA STUDIES

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus prof. dr. ir. J. T. Fokkema,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen op dinsdag 13 januari 2009 om 15.00 uur

door George VAN LEEUWEN
geboren te Alphen aan den Rijn.

Dit proefschrift is goedgekeurd door de promotoren:
Prof. dr. A.H. Kleinknecht
Prof. dr. B.M. Balk

Samenstelling promotiecommissie:
Rector Magnificus, voorzitter
Prof. dr. A.H. Kleinknecht, Technische Universiteit Delft, promotor
Prof. dr. B.M. Balk, Erasmus Universiteit Rotterdam, promotor
Prof. dr. C.P. van Beers, Technische Universiteit Delft
Prof. dr. E.J. Bartelsman, Vrije Universiteit Amsterdam
Prof. dr. E. Brouwer, Universiteit Tilburg
Prof. dr. P. Mohnen, Universiteit Maastricht
Dr. A.P. Poot, Universiteit Utrecht
Prof. dr. J.P.M. Groenewegen, Technische Universiteit Delft (reservelid)

Innovation and performance. A collection of microdata studies
George van Leeuwen
Proefschrift Technische Universiteit Delft.
Met samenvatting in het Nederlands
ISBN 978-90-8559-478-9
Trefwoorden: R&D, Innovatie, ICT, productiviteit

Printed by Optima Grafische Communicatie, Rotterdam
Cover design: Hanneke van Leeuwen, Transisters Rotterdam

Correspondence to: georgevanleeuwen@hetnet.nl

Preface

There are still many puzzles to be solved concerning the relation between innovation and firm performance, in particular concerning the distinct roles of information and communication technology (ICT) and Research and Development (R&D) in creating new or improved products or production processes. This thesis provides evidence that both instances of innovation are important drivers of productivity and, thus, economic growth. This book consolidates the results of empirical work covering about 10 years of research aimed at understanding the importance for firm performance of innovation in a broad sense.

Looking back over the last 10 years, and the years before, there is much to be grateful for. First of all, I would like to express my gratitude to my employer Statistics Netherlands for giving me the opportunity to do things that are so distant from the core business of statistical agencies and for such a long time. Almost during my entire career at Statistics Netherlands I have been able to do research on firm-level data. It started early enough to witness the shift from macro data oriented research to research that placed individual firms at the centre of interest. To a large extent, this shift was also technology driven, as technological opportunities enabled the increased availability of data sources and the development of computational and econometric methods for analyzing large data sets, covering data referring to what is now considered to be the preferred level of analysis for many types of economic research.

Success has many fathers and with such a long period to reflect on, it would require a separate book to give everybody the credits they deserve. Thus, I am aware that I cannot do justice to all. I am especially grateful to Peter Kooiman and Johan Lock for their pioneering efforts to introduce micro data research in the statistical office. Probably, Peter will not be aware of this, but without his enthusiastic and inspiring method of teaching the econometric courses that I attended at the Erasmus University, my career certainly would have taken a completely different path.

I am also very much indebted to Bert Balk and Kees Zeelenberg for providing an excellent research environment during the period that I joined the Statistical Methods Department of Statistics Netherlands. The foundations for much of the work included in this thesis were laid during the period that I was working as a researcher at the Centre for Research of Micro-economic Data (CEREM) in the years that Bert was director of this Centre. Special thanks also go to Eric Bartelsman for his support to proceed with microdata research (both tacit and more explicit in joint research projects) in times that microdata research was considered less important within the office. Without his continuous efforts, microdata research would not have obtained today's important status, not only in the Netherlands but also world-wide. I also owe much to Henry van der Wiel and Henk Kox, not only for the pleasant and fruitful cooperation during my stay at CPB Netherlands Bureau for Economic Policy

Analysis, but also for their permission to include our joint papers in this thesis. Similar thanks go to Luuk Klomp, who co-authored two papers on innovation during the first years that Statistics Netherlands was responsible for collecting innovation data. Last, but not least, I thank Alfred Kleinknecht for giving me the opportunity to defend this thesis at the Delft University of Technology, and Alfred and Bert for encouraging me to complete this thesis.

George van Leeuwen
October 2008

Contents

Chapter 1

Introduction

1.1 Motivation

This thesis collects six papers dealing with the use of firm-level data for investigating various dimensions of firm performance. The first three papers relate firm performance in manufacturing to innovation. Next, two papers deal with the relation between Information and Communication Technology (ICT) and productivity in manufacturing and business services. The final paper discusses the issue of scale effects in business services.

The common theme of these papers is the search for drivers of firm performance in renewing economies. Firm performance is measured as productivity (growth). Productivity (growth) has been an important field of research in the past decade. It became an important policy and research issue because of the perceived divergence of growth performance between European countries and the US in the second half of the previous decade, when US expanded its productivity lead over European countries. The exceptional productivity performance of the US during 1995 – 2000 took place in a time span that was labeled 'new economy' and that was characterized by a rapid diffusion of ICT technology. Examples are the diffusion of the internet and mobile telephony. These developments increased the interest in the analysis of economic growth and the causes behind differences in productivity (growth) across countries and within countries between firms. In policy circles the question was raised how to bridge the gap with the US and how to achieve sustained economic growth with more and better jobs and greater social cohesion in societies which, in addition, face the problem of an ageing population. These are the primary goals of the so-called Lisbon strategy formulated in 2000 for EU-countries.

1.1.1 R&D and ICT

The interest in the drivers of economic growth is not entirely new. The new thing was the focus on the role of ICT as a vehicle of technological progress that is embodied in computers. This special form of technological progress started more than 50 years ago with Research and Development (R&D) of Intel, which enabled the creation and further advancement and application of microprocessor technology. Since 1965 the speed of microprocessors doubled every two years and even more rapidly since 1995. The steep decline in prices of ICT hardware (among others due to increased competition between producers of ICT goods) and the growing scope for application of ICT technology has made ICT one of the most dynamic areas of investment as well as one of the most pervasive technologies.

This brief summary demonstrates the important role of R&D for creating and accelerating (the diffusion of) technological progress and for cumulating the innovation process in general. This example also explains why innovation and technological change in a small country such as the Netherlands is largely based on R&D performed abroad. In addition, it also stresses that the meaning (concept) of innovation has been broadened in the course of time. Innovation can no longer be conceived as a R&D story alone, as the adoption of technologies developed elsewhere can be seen as a substitute for performing own R&D.

Nevertheless, it is often stated that own R&D or basic research remains the key to technology adoption and the best way to narrow the gap with technological leaders. In this view, investing in own knowledge is a pre-requisite for capturing the fruits of knowledge developed abroad and a necessary condition for creating own technological innovations in order to remain on a competitive edge in an economic environment that is increasingly governed by globalization of production as well as competition. Moreover, asserting that R&D directly or indirectly contributes to productivity (growth), explains the importance of a continuous search for new (national) policy instruments or for adapting existing policy instruments in order to enhance the upgrading or the maintenance of existing knowledge bases.

1.1.2 ICT and innovation

The potential of R&D to enhance product innovation, and the assessment of the contribution of R&D and other determinants of technological innovations to productivity (growth) are the subject of the first three papers of this thesis. By way of contrast, the other papers focus on the contribution of ICT to productivity, and the explanation of differences in productivity between important users of ICT technology (the business services sector). In these papers the relation with innovation is studied from the other side, by highlighting the special features of ICT as a general purpose technology. The use of ICT can make innovations more effective along different channels. It enables firms to customize services offered, to reduce inefficiency in the use of other inputs (e.g. by reducing inventories or by streamlining other business processes, for example via reorganizations), or to seize spillover effects generated by ICT networks. Business services are an important example of how ICT diffusion can transform economies whose production has become increasingly foot-loose, non-physical or intangible. The rapid growth of ICT-enabled services around the world demonstrates that previously sheltered sectors are increasingly more exposed to outsourcing and international competition, not in the least due to the increased use of ICT. This trend calls for the need to foster innovation in services as well as for adjusting the regulatory environment of service firms. The last issue is the subject of the final chapter of this thesis. Here, productivity differences within the European service sector are linked to scale-related optimality of service production. Next, the relation between (scale-related) X-inefficiencies and country-differences in the regulatory environment of business service firms is investigated.

1.2 Literature background

Although the papers focus on firm performance, the motivation for conducting these studies can be understood better by beginning with a macro view on the relation between innovation[1] and aggregate productivity growth. The theoretical developments started about 20 years ago with the launching of the endogenous growth theory (Romer, 1986). This theory originated from the critics that neo-classical theory failed as a theory of economic development. The basic assumption of the (standard) neo-classical model is that technological change is exogenous and that the long-run pattern of economic growth is governed by the accumulation of reproducible capital. In this view differences in aggregate savings rates translate into permanent differences in (aggregate) income levels.

The response of the endogenous growth theory can be broadly divided into two classes: 1) competitive models that renewed the role of capital accumulation and 2) non-competitive R&D models or – more generally – innovation-based growth models. The first class of models focuses on the decision of firms to accumulate capital, either tangible or intangible in nature. The key feature of these models (see e.g. Romer, 1986 and Rebelo, 1991) is that, at the aggregate level, there are no diminishing returns to reproducible capital. This is asserted by lumping together capital accumulation and technology. These so-called AK models[2] acknowledge that capital accumulation is an important vehicle of technology adoption, because technology adoption in one way or another is represented in the accumulation of (intangible) capital. Therefore, capital accumulation remains the basic driver of economic growth, and not innovation as such. With appropriate policy institutions, capital can move freely around the world so there is no need to deviate from the assumption of competitive markets. This last feature distinguishes the AK models from the second class of endogenous growth models.

The second branch of the endogenous growth literature (see e.g. Romer, 1990, Grossman and Helpman, 1991) consists of papers that focus on the decisions of firms to conduct research and development (R&D) in a non-perfectly competitive environment. Deviations from perfect competition arise because of the attribution of some monopoly power to successful innovators. Without the potential to finance R&D from retained profits, no self-interested agent would be willing to engage in costly R&D. In this story, cumulating the innovation process is the engine of growth and the persistence of profits is assumed to be a pre-requisite for capturing increasing dynamic returns to innovation, and to support and reinforce the innovation process. Here, the central message is that policies should be directed to improving the conditions for performing R&D, e.g. by protecting property rights or by providing financial incentives (subsidizing R&D) or by refraining from competition policies that entail the risk of eroding post-innovation rents.

[1] Being intrinsically an example of a major technological innovation, there is no need to treat ICT apart at this stage.

[2] A represents the technology parameter and K is the capital input of the production function.

Although endogenous growth theories provide a richer description of the fundamental forces underlying economic growth than the exogenous (neo-classical) growth theory, their success is not undisputed. An important reason for this is that endogenous growth models also do not give a fully satisfactory account of the stylized facts. An important example concerns the post-war labor productivity growth experience of Europe versus the US, with Europe first catching up (before 1990) and next lagging behind the US. This pattern can be explained neither by different capital-labor ratios (in Europe on average higher than in the US since 1990) nor by different R&D intensities (in the US higher than Europe before 1990).

Aghion and Howitt (2006) argue that an important reason for the failure of the endogenous growth theories is the lack of a sound micro-economic basis. By introducing important insights from the theory of industrial organization they show that endogenous growth theory can be adapted to give a better account of stylized facts as well as deliver useful guidelines for designing policy instruments. The basic idea is that growth processes are best explained by starting from a continuous process of creative destruction that is fueled by the interplay between innovation and competition. A new element is that potential entry changes the balance between innovation and competition as entrants can be better placed than incumbent firms with respect to the introduction of new technology.

In the Schumpeterian model, innovation remains the basic driver of productivity growth. However, and contrary to the earlier endogenous growth models, the Schumpeterian paradigm provides a more comprehensive account of the role of innovation for explaining patterns of productivity growth because it makes a distinction between (productivity growth of) 'real' innovators and innovation imitators. This distinction also makes more explicit that observed aggregate productivity growth results from a continuous process of pushing up the technological frontier and catching up to the frontier either by introducing 'leading edge' innovations or by implementing innovations that have been developed elsewhere. In such a story there is no reason to believe in permanent differences of productivity levels, nor in permanent growth differentials. Thus, besides encompassing earlier models of the endogenous growth literature, the Schumpeterian model has the virtue of providing a more realistic picture of the main forces that are driving productivity growth, both at the firm level and at the aggregate level.

This brief historical overview of the (endogenous) growth literature can be used to make the step to the subject of this thesis, i.e. the use of firm-level data for understanding the relation between innovation and firm performance. An important conclusion that can be drawn at this stage is that macro theories these days start from 'heterogeneous' producers instead of a 'representative agent'. This implies that the empirical testing of these theories requires firm-level data. Indeed, today many contributions to the empirical literature on endogenous growth are using firm-level data. This is in particular relevant for testing the contribution of innovation to firm performance, as own innovations are not the only source of productivity growth for all firms.

'Going down' to the firm-level, it can be easily verified that many firms are not permanently engaged in performing R&D, but – nevertheless – show up to be more productive than firms that perform R&D on a permanent basis. A more complete picture emerges if one takes into account that productivity growth also arises from using inputs more efficiently. The usual way to quantify the impact on output of using more or less inputs is doing 'growth-accounting'. This exercise is often conducted at the industry or macro level with the purpose of delivering e.g. an estimate for the contribution of ICT capital deepening to labor productivity growth. However, the change in the ICT capital intensity at the industry level arises from changes in the ICT capital intensities of incumbent firms as well as differences between ICT capital intensities of exiting and entering firms. Again, competition-driven selection of good and bad performing firms may play a dominant role here. Firm-level data are imperative for understanding the importance of each of these factors.

Returning to innovation, similar conclusions can be drawn when evaluating the literature on firm-level innovation data. Much progress has been made with regard to understanding the link between the characteristics of technology regimes and innovation patterns observed at the firm level.[3] An empirical regularity found in this strand of research is the skewness of R&D distributions. This skewness results from the co-existence of many firms spending little (or even nothing) on R&D and relatively few (large) firms that carry out the bulk of aggregate R&D. Such a pattern can be explained by the different types of knowledge underlying innovations. If this knowledge is specific, codified and 'simple', then technology adoption is easier and less costly than in case of generic, tacit and complex knowledge, which calls for investing in the creation and maintenance of own knowledge bases. Dependent on these conditions, one may expect that the need to perform R&D and the way innovation processes are organized can differ greatly between firms.[4] In addition, this also explains why the probability of realizing innovation success does not depend on performing R&D only.

Taking stock, identifying the contribution of innovation to productivity (growth) remains a difficult task for at least three reasons: 1) productivity (growth) at the firm-level cannot be attributed exclusively to own performed innovation or R&D, 2) besides performing own innovations or R&D, capital deepening also remains an important source of productivity (growth) as this is a vehicle for (embodied) technology adoption, and 3) being successful in innovation cannot be attributed to a single factor like R&D.

[3] An important reference is Malerba and Orsenigo (1995).

[4] In the literature these different characteristics of knowledge bases mirror the distinction between the Schumpeter Mark I and the Schumpeter Mark II innovation regimes. In the Schumpeter Mark I regime the emphasis is on small firms as the most important drivers of innovation, whereas the Mark II regime is assumed to be better applicable to large R&D performers.

Nevertheless, the R&D (innovation) productivity literature has a long tradition. This strand of research owes much to Griliches.[5] He started (in 1957) by introducing the concept of R&D capital as a separate input into production. The application of this R&D capital model has been the standard approach to the assessment of the R&D contribution to productivity growth in many applications and for many years. Not in the least due to the scarcity of data, there was little scope for improving substantially on the model specification[6] or for refining the measurement of inputs into innovation. In spite of the increased use of sophisticated estimation techniques (e.g. panel data techniques to control for firm-specific effects) many conceptual and empirical problems could not be dealt with in a satisfactory way.

An important heritage of the work of Griliches concerns the introduction of the so-called 'innovation production function'. This theoretical construct asserts that innovation can be best characterized as a separate production process with R&D and other factors used as inputs for the production of new or improved products. The adoption of this construct had two implications: 1) the assessment of the link between innovation and overall firm performance should preferably start from a structural model because this enables a better understanding of the various factors that play a role, and 2) new data had to be collected on the realization of innovation output and for providing a richer description of the innovation process than does R&D alone.

The introduction of Community Innovation Surveys (CIS) opened a window of new opportunities for innovation research. A seminal paper that explores this new route is the study of Crépon, Duguet and Mairesse (1998). Since then, several contributions to the literature have taken this paper as the starting point for replicating and refining the 'CDM model'. Three examples are presented in this thesis. Their contribution to the literature will be outlined in the next section.

1.3 Main contributions

As to the contribution to the literature, a distinction must be made between the innovation chapters and the other chapters of this thesis. I start with the contribution of the innovation papers (Chapters 2, 3 and 4 of this thesis). These papers contribute to the literature as follows:

1) Extending the CDM model, the joint dependence of innovation inputs and innovation output on innovation characteristics is taken into account more explicitly. This is achieved by estimating the equations for innovation inputs, innovation output and firm performance simultaneously and by using more variables that potentially characterize innovation processes. This extension is considered to be useful as the literature has not been conclusive

[5] See Griliches (2000) for an account in retrospective and the references mentioned there.
[6] A notable refinement of the 'baseline' model concerned the extension of the model with R&D spillover capital in order to distinguish between private and social returns to R&D.

on the role of specific factors that (conditional on being innovative) affect the level of innovation inputs (measured by R&D- or total innovation expenditures) as well as the throughput stage of the innovation process simultaneously (their complementary contribution to innovation output).

2) The CDM model is extended by including a feedback link that runs from a firm's total sales growth to innovation. Thus, Schmookler's demand pull hypothesis could be tested in a more comprehensive framework than previously.
3) The assertion that a firm's market power (the ability to increase market shares) also depends on the degree of product differentiation has been incorporated in the CDM model by using innovation output as 'demand-shifter'. Besides enhancing the interpretation of the estimate of innovation output in production function models, this approach also forwards the reasoning of Klette and Griliches (1996) that productivity growth measured at the firm level is likely to be biased if deflation methods do not account in a satisfactory way for product differentiation.
4) The dynamic interdependencies for innovation considered from the input side as well as from the output side of the innovation process have been investigated by using two waves of CIS and by adopting a dynamic model for innovation inputs and innovation output.

In the ICT papers of the thesis (Chapters 5 and 6), the emphasis is not on innovation as such, but on the interaction between capital accumulation and innovation. ICT is an excellent example to investigate this issue. In essence, investing in computer hardware (and software) can be seen as a form of adoption of technology as far as embodied in capital. The ICT papers of the thesis contribute to the literature by using enhanced production function models in order to estimate the contribution of ICT externalities to productivity growth. A distinction is made between 'internal ICT spillovers' (the ICT link with other innovation processes carried out within the firm, e.g. the streamlining of business processes via reorganizations) and 'external spillovers' (the productivity impacts arising from the ability to pick the fruits of ICT investment outside the firm). The papers also explain why 'growth accounting' results can be different from econometric estimates for the ICT-contribution to productivity growth.

The final chapter underlines the importance of using 'institutional' data for appraising inter-country productivity differences. It contributes to the literature in two ways: 1) the presence of local scale effects in business services is investigated by applying a frontier model and 2) it is investigated to which extent X-inefficiencies (distances to the best-practice frontier) in business services are related to different policy institutions.

1.4 Reader's guide

Chapter 2 combines the innovation model of Kline and Rosenberg (1986) with the CDM (1998) model to evaluate the importance of new CIS innovation variables for the contribution of innovation to sales growth and employment growth. The 'chain-link innovation model' of Kline and Rosenberg (1986) is used as a framework for investigating the interdependencies of the different stages of the innovation process and the link between innovation and firm performance. This link is analyzed in two directions 1) the contribution of innovation output to sales and employment growth and 2) the feedback links running from a firms' sales growth performance to the innovation process. In this paper the relationships between the different stages of the innovation process and the two mentioned measures of overall economic performance are analyzed with the method of Full Information Maximum Likelihood (FIML).

In Chapter 3, the focus is on the explanation of the contribution of innovation to multi-factor productivity (MFP) growth. By using similar variables as in Chapter 2, this chapter elaborates on the importance of innovation induced product differentiation for assessing the contribution of innovation to MFP growth (either measured in gross output or in value added terms). To achieve this objective, the revenue function approach of Klette and Griliches (1996) has been implemented in the CDM framework, thereby enhancing the interpretation of the contribution of innovation to productivity growth. Furthermore, other estimation techniques than FIML were applied in order to investigate the robustness of the estimates for the returns to innovation output of innovation investment and the contribution of innovation output to productivity growth.

Chapter 4 presents a first attempt to estimate the persistence of innovation. Using two waves of the CIS, this chapter integrates the models for knowledge accumulation of Hall and Hayashi (1989) and Klette (1996) in the CDM framework. Similar to the preceding chapters, the CIS data are used to control for the complementarities of internal and external knowledge bases. The dynamics of innovation is investigated by implementing simple dynamic specifications for R&D inputs (R&D expenditures as a share of total sales) and innovation output (measured as the share of new products in total sales). A problem of using two waves of CIS concerns the missing R&D history of firms that stated to have created new products in the last wave, but were not surveyed in the preceding wave. For this reason, and in order to investigate the robustness of the estimates for the contribution of innovation to MFP growth, the model is re-estimated using a broader measure of innovation output (including incremental innovations) and by comparing the contributions to MFP growth of the dynamic model with the same estimates obtained from a static innovation model in which the two waves are pooled.

In Chapters 5 and 6, the focus is on the contribution of ICT to MFP growth. Both chapters deal with the problem that ICT can affect productivity growth via various channels. ICT related productivity growth can arise as a result of ICT capital deepening (using more computers per employee), but also as a result of (innovation) externalities induced by ICT use. This last feature of ICT investment could not be taken into account satisfactorily in the (many) 'growth-accounting' exercises that were conducted in the previous decade and that used industry data or data for the whole economy. It also explains why the contribution of ICT to labour productivity growth has been debated so much in the previous decade. Thus, in essence, Chapters 5 and 6 elaborate on the problem of how to divide the contribution of ICT to labour productivity into a capital deepening contribution and a MFP contribution (output growth corrected for increased (ICT) capital inputs). The emphasis in these chapters is on productivity growth in business services (wholesale trade, retail trade and commercial services), because ICT is considered to be more important in these branches than in manufacturing.

Chapter 5 analysis the contribution of ICT to labour productivity growth by comparing estimates for this contribution derived from standard production function models with those of 'growth accounting' models at the firm-level. Subsequently, the differences between the results of these 'parametric' and 'non-parametric' approaches are investigated more profoundly by adding innovation and ICT spillover indicators to the production function model. The interaction between ICT and innovation is also explored in Chapter 6. Besides placing the results of Chapter 5 in a broader perspective, this chapter also elaborates more explicitly on the topic that ICT technology (being an example of capital embodied innovation itself) and other innovations are complementary, and that investing in ICT also contributes to productivity growth in an indirect way by being an 'enabler' of other types of innovations. This assertion is investigated e.g. by estimating models that take into account the interaction of ICT and reorganizations at the firm-level.

In Chapter 7 the importance of scale economies for productivity in business services is investigated. The business-services sector is a rapidly growing industry that has important links with other industries. Some parts of the sector are very knowledge intensive. Furthermore, although many firms are still oriented at national markets, there is an increasing trend of globalization of production. The scale issue arises because many firms are small and might perform at a sub-optimal scale. As the business-services sector is an important supplier of intermediary inputs, improving on scale economies could 'spill over' to the productivity performance of other sectors It is investigated whether differences in scale economies can be related to market characteristics and institutional factors such as product market regulation or entry barriers. This is executed by applying a generalized stochastic frontier model to international cross-sectional data.

1.5 Picturing the framework of the thesis

This section presents an overview of the framework underlying the various chapters by using a stylized and augmented input-output model. See Figure 1.1[7]

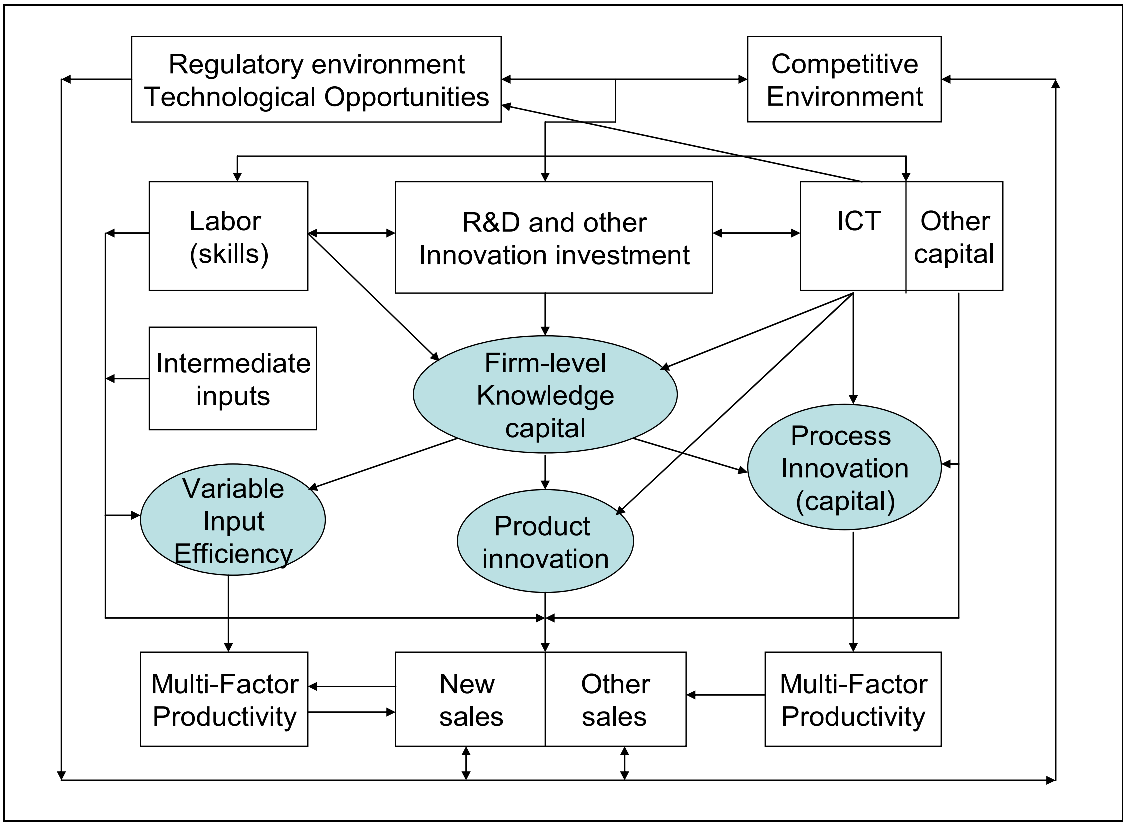


Figure 1.1: Innovation and firm performance

To analyze firm performance, a natural starting point is to look at a firm's environment. This is taken into account by the two upper blocks and the arrows that shape the 'outer loop' of the model. At the start of operations a firm's competitive and regulatory environment and the technological opportunities are assumed to be given. Examples are the existence of financial incentives to invest in R&D or other capital inputs, the existence of product-market regulations or entry-preventing barriers to competition. The regulatory environment of firms (or more generally the policy institutions that are in place) can affect the competitive environment and this link can also be reversed. For this reason, I have included a link between the two blocks that runs in both directions.

The second layer of the figure represents the primary inputs into production, whereas the third 'level' of the model, consisting of the shaded parts, points to the throughput stage of the CDM innovation model. Under the assumption of perfect competition, one can think of a direct

[7] The figure extends the one in CDM (1998). Among others, this extension concerns the inclusion of ICT as a separate knowledge input and the inclusion of feedback links.

link with exogenously given market conditions and the sales performance of our hypothetical firm. Thus, when leaving out the shaded innovation parts of the figure, the model resembles the standard KLEMS model, frequently used for the non-parametric estimation of Multi-Factor Productivity (MFP).[8] In this view, MFP is often interpreted as a measure of technological capability whose main driver is investment in R&D and other innovation related sunk costs.

Although treated similarly as other capital inputs in growth-accounting studies, I have included ICT as a separate input into production, because of its special features. In contrast to other capital inputs, ICT capital embodies a set of general purpose technologies that enable a firm to seize the benefits of internal spillovers. Internal spillovers refer to the potential of ICT to increase the efficiency of the use of other inputs. Moreover, ICT enhances product innovation as well other forms of process innovation. In the figure this is taken into account by assuming that ICT contributes to knowledge capital in a way that resembles investment in R&D.[9] The second reason to focus on ICT, concerns the capability of ICT to create network externalities. The potential of a firm to seize the benefits of external ICT spillovers will increase with the level of ICT use of clients, customers and suppliers (i.e. with the technological opportunities offered by its environment). A symmetric reasoning calls for the inclusion of a backward linkage, as the own level of ICT use of a firm can affect the technological opportunities of other firms. However, investing in computer hardware is not a sufficient condition to capture the full fruits of ICT technology. Making ICT productive also calls for investing in complementary factors. In the figure this is implemented by including a link running from labor (skills) to knowledge capital. With respect to ICT, this link is assumed to represent more than only computer skills of the labor force available. Other labor-related factors such as managerial capabilities or organizational practices can also be interpreted as the use of (special types of) labor skills.

The central part of the model runs from the R&D (and other innovation) investment block to the sales performance of our hypothetical firm. In essence this is the core of the CDM model, which asserts that the innovation process can be seen as a separate production process that establishes a link between inputs into innovation and firm performance, either measured by sales performance or by productivity. In the CDM model, the importance of product innovation is measured by the share of new and/or improved sales. In the figure I highlight the role of new sales. Generating new sales can be seen as a way to rejuvenate product lines, which, in turn, enhances sales opportunities as well as profitability. Thus, 'real' innovations are assumed to have a greater potential to increase market power than do innovation imitations. In both cases, it

[8] The KLEMS model makes a distinction between physical capital (K), labor (L), energy (E), material (M) and service (S) inputs. E, M and S together are called 'Intermediate inputs'.
[9] This view is also reflected in the design of the so-called Knowledge Module of the System of National Accounts that aims at a distinction between knowledge capital and other capital inputs. In this module ICT investment is a separate component of aggregate knowledge capital.

is assumed that product innovation is an important vehicle to remain on a competitive edge. For this reason one may expect a feedback link that runs from a firm's own sales performance to its competitive environment. This 'closing' link also serves as the starting point for looking at the determinants of firm performance in a dynamic setting. Comparing the figure for two (adjacent) periods enables us to elaborate on the sources of Multi-Factor Productivity growth and their contribution to output growth, which, in essence, is the main objective of doing 'growth-accounting'. For this reason, I also include a link running from MFP (growth) to output (growth).[10]

Keeping this dynamic extension in mind, the bottom line of the figure is that Multi-Factor Productivity growth is a multi-faceted, not purely physical phenomenon. MFP growth at the firm-level has to do with various internal as well as external factors, each of which can be influenced in some way by innovation in a broad sense. MFP-growth can mirror innovation induced efficiency change, increased market strength as a result of product innovation, an increase in the potential to seize the benefits of network externalities facilitated by higher levels of ICT use of other firms or even reflect changes in policy institutions that favor different firms in different ways. Analyzing the importance of some of these factors is the subject of the coming chapters.

References

Aghion, P. and P. Howitt, 2006, Appropriate Growth Policy: A Unifying Framework, Joseph Schumpeter Lecture, *Journal of the European Economic Association*, vol. 4(2-3), pp. 269 – 314.

Crépon, B., E. Duguet and J. Mairesse, 1998, Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level, *The Economics of Innovation and New Technology*, vol. 7, pp. 115–158.

Griliches, Z., 2000, *R&D, Education and Productivity, A Retrospective*, Harvard University Press, Cambridge Massachusetts, London, England.

Grossman, G., M. and E. Helpman, 1991, Quality Ladders in the Theory of Growth, *Review of Economic Studies*, vol. 58, pp. 43–61.

Hall, B., H. and F. Hayashi, 1989, Research and Development as an investment. *NBER Working Paper no. 2973*, National Bureau of Economic Research, Cambridge, Mass., USA.

Kline, S.J. and N. Rosenberg, 1986, *An overview of innovation, in Landau, R., and N.Rosenberg, (eds) The Positive Sum Strategy*. Harnessing Technology for Economic Growth, National Academy Press, Washington DC.

[10] Sales growth equals gross output growth in the absence of changes in inventories.

Klette, T., J. and Z. Griliches, 1996, The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous, *Journal of Applied Econometrics*, vol. 11, pp. 343– 361.

Klette, T., J., 1996, R&D, Scope Economies, and Plant Performance, *RAND Journal of Economics*, vol. 27, no. 3, pp. 502 – 522.

Malerba, F. and L. Orsenigo, 1995, Schumpeterian Patterns of Innovation, *Cambridge Journal of Innovations*, vol. 19, pp. 47–65.

Rebelo, S., 1991, Lon-Run Policy Analysis and Long-Run Growth, *Journal of Political Economy*, vol. 99 (3), pp. 500–521.

Romer, P., 1986, Increasing Returns and Long-Run Growth, *Journal of Political Economy*, vol. 94 (5), pp. 1002–1037.

Romer, P., 1990, Endogenous Technological Change, *Journal of Political Economy*, vol. 98 (5), part 2, pp. 71–102.

Chapter 2

Linking innovation and firm performance: a new approach*

Abstract

Using the second Community Innovation Survey (CIS-2) for the Netherlands we analyse the input and output stages of the innovation process and the links between the innovation process and overall economic performance. We investigate the existence of feedback links running from past economic performance to the input and the output stage of the innovation process and compare the results of a single-equations approach with the results obtained from a simultaneous-equations model.

2.1 Introduction

The recognition of knowledge being an important production factor becomes more and more widespread. The spate of literature from policy makers and scientists alike is a good indicator for the interest in the knowledge-based economy and thus in the innovation process (see e.g. Kleinknecht, 1996, Brouwer, 1997, Acs et al., 1999, and Audretsch and Thurik, 1999). The availability of new and improved indicators collected in the Community Innovation Surveys (CIS) opened the opportunity to study innovation as a separate process with R&D expenditures as the most important input into innovation and newly created or improved products or process innovation as the output of the innovation process. The data referring to the technological environment of firms and to the organisational aspects of their innovation processes created a major impetus for the explanation of differences in innovation activity as well as an analysis of the importance of firm-specific innovation characteristics for the output of the innovation process and the effects of the innovation output on firm performance.

Recently, the interest in the innovation process has shifted away from the input (R&D) to the output stage (realised innovations). Moreover, the focus is now also on the linkages between the three stages of the innovation process: input, throughput and output, with the role of innovation as a driving factor of long-term macro-economic growth taken for granted.

The importance of feedbacks from overall firm performance to the level of innovativeness has been one of the subjects of various innovation studies. Recent tests of the so-called demand pull hypothesis of Schmookler (1966) are presented in e.g. Brouwer and Kleinknecht (1997, 1999) and Cosh et al. (1999). These studies have in common that one stage of the innovation process (for instance R&D expenditures or the realisation of innovations) has been isolated and subsequently linked to economic performance, thereby neglecting the joint dependence of

* This chapter, co-authored by Luuk Klomp, appeared in *International Journal of the Economics of Business*, vol. 8, 2001, pp. 343–364. I am are thankful to Bert Balk, Jos van Deventer, Niels de Lanoy Meijer, Sjaak Pronk and participants of the CAED'99 conference (The Hague, The Netherlands, August 1999) for helpful comments and an anonymous referee for helpful suggestions.

measures of innovativeness on firm specific innovation characteristics or the joint dependence of innovative output and the overall economic performance of firms.

In this paper we analyse the relationships between the different stages of the innovation process and overall economic performance using a simultaneous-equations model. To this end we use the ‘chain-link model’ of Kline and Rosenberg (1986) as a frame of reference. In our view the use of simultaneous-equations models that cover both the innovation process and (the overall) firm performance has two advantages compared to the single-equations approach. Firstly, the effects of the technological environment on a firm’s innovation process can be disentangled in two parts: an impact on the innovation input and an impact on innovation output. Secondly, a simultaneous-equations approach is more adapted to models that stress the importance of feedback links running from overall economic performance and the innovation process.

The approach presented in this paper can be compared with other recent innovation studies which take account of the simultaneity problem. Contrary to e.g. Lööf and Heshmati (2000) and Crépon et al. (1998) we do not use a production function framework. In these studies innovation has been incorporated in the traditional R&D production function approach by using a structural model in which the R&D capital stock is assumed to determine the level of productivity indirectly, i.e. via its impact on innovation output. R&D capital stocks are not available in our data. Moreover, we believe that innovation is more than formal R&D only. For these reasons we follow a different route by choosing the innovation intensity as input for the production of innovative output and turnover and employment growth as our measures for firm performance.

For the application of the full model we need a complete set of innovation variables and performance measures. These are obtained by linking different data sources. Common to other studies, the linking of data from different sources raises missing variable problems. In our study we also face a special missing variable problem due to the fact that the key variable ‘innovation output’ has not been measured for the innovating ‘service firms’ and this may show up as a selectivity problem in the estimation procedure. Following Lööf and Heshmati (2000) and Crépon et al. (1998) we try to take account of selectivity as well as simultaneity biases by incorporating the correction for selectivity in the estimation procedure for the full model.

It is shown that the (relative) importance of variables referring to the technological environment and firm specific innovation characteristics diverges from the estimated impacts of the single-equations approach when taking into account the simultaneous nature of the variables. Furthermore, the estimate of a feedback from past economic performance to the innovation process appears to be more pronounced when one takes into account the joint dependence of the different stages of the innovation process and overall firm performance.

The plan of the paper is as follows. In section 2.2 we describe the construction of the data and present a brief summary of the results for the used measures of firm performance. It is shown that innovative firms outperformed their non-innovative counterparts, although the differences for turnover growth are more pronounced than those for employment growth. Section 2.3 discusses how the model of Kline and Rosenberg has been used as a guide for setting up our model. The identification of our model requires some a priori assumptions on the specification of the equations and the choice of the exogenous variables. These topics and the related selectivity issue are discussed in section 2.4. The estimation results are presented in section 2.5 and section 2.6 closes with a summary and the most important findings.

2.2 The data

2.2.1 Matching CIS-2 and the Production Survey data

In this subsection we outline the procedure followed to select the data used in the econometric part of the paper. As a starting point we used all the 10664 firms that responded to CIS-2, which covers the period 1994 – 1996. The majority of these firms were also covered in the Production Surveys of Statistics Netherlands, which provide data on e.g. total sales, employment, value added and profitability. However, a number of responding firms belong to sectors for which no Production Surveys were available, and for these firms use had to be made of the data on total sales and employment in 1994 and 1996 that were collected in CIS-2. We used the data on employment in 1996 collected in CIS-2 for all firms in order to check the comparability of the unit of observation in both surveys. On the basis of this consistency check it was decided to reject 1250 firms because of the large discrepancies in the employment figures. In addition we omitted 1032 firms from the analysis because their data on total sales and employment were missing in the Production Surveys of 1994 or 1996 and 54 respondents to CIS-2 were rejected at this stage because of an implausible score for their innovation intensity.[1] After this preliminary data cleansing 8328 firms were selected with a complete record of total sales and employment for 1994 and 1996. In total 3995 of these firms stated to have implemented product or process innovation. However, as a consequence of the choice of the exogenous variables, not all innovating firms could be used in the estimation procedure. In total 936 firms had to be rejected due to missing data for the exogenous variables.[2] For the remaining 3059 firms data on the inputs into innovation were available and 1977 firms of this sub-sample also had data for the share of innovative products (‘new and improved to the firm’) in total sales, including the firms that reported zero innovative sales (N = 280) and the firms with sales in 1996 consisting entirely of new or improved products (N = 35). Furthermore, we recall that this measure for innovation output is not available for all firms belonging to the 'service' industries.

[1] Firms were rejected if the ratio of total innovation expenditure to total sales was higher than 50 percent.
[2] For 917 firms data on profitability and in 17 cases data on the age in January 1994 were missing and 2 firms were rejected because of an exceptional score for the profitability indicator.

Table 2.1 The selection of firms starting from the Production Survey (PS) data

Sector of principal activity and classes of firm size[a]	Number of firms with data on sales and employment	Of which:			
		Non-innovating firms	Innovating firms used in the model	Firms with innovative output available	R&D firms
Manufacturing	*2969*	*1002*	*1820*	*1820*	*979*
Small firms	1296	607	651	651	227
Medium sized firms	1313	345	894	894	552
Large firms	360	50	275	275	200
Services	*4170*	*2496*	*1082*		*372*
Small firms	1852	1264	346		81
Medium sized firms	1892	1076	550		196
Large firms	426	156	186		95
Other industries[c]	*1189*	*835*	*157*	*157*	*23*
Small firms	529	402	69	69	6
Medium sized firms	573	392	66	66	10
Large firms	87	41	22	22	7
All sectors	*8328*	*4333*	*3059*	*1977*	*1374*
Small firms	3677	2273	1066	720	314
Medium sized firms	3778	1813	1510	960	758
Large firms	873	247	483	297	302

[a] Small firms: firms employing more than 10 and less than 50 employees;
Medium sized firms: firms employing 50 or more and less than 200 employees;
Large firms: firms employing 200 or more employees;
[b] Firms with a measurement for the share of products 'new to the firm' in total sales of 1996;
[c] This sector includes the following industries: agriculture, forestry and fishing, mining, electricity, gas, and water and the construction industry.

Table 2.1 presents a breakdown of the initially selected firms according to some response characteristics. About 48 percent of the selected firms consist of firms that stated to have implemented product or process innovations in 1994 – 1996. The rate of innovativeness (measured by the number of innovating firms as a percentage of all firms) varies between 66 % for manufacturing and 30 % for 'other sectors' and is increasing with firm size in all sectors. It can be verified that, contrary to rate of innovativeness which increases with firm size, the share of firms reporting to have realised innovative output does not differ very much between classes of firm size. Thus, conditional on having implemented product or process innovation, the extent of innovation success seems not to depend on firm size at first sight. Finally, Table 2.1 indicates the well-known empirical fact that formal R&D activities are predominantly concentrated in manufacturing and that the probability of performing R&D on a permanent basis also is size dependent.

Figure 2.1.a The distribution of total sales growth (n = 8328)

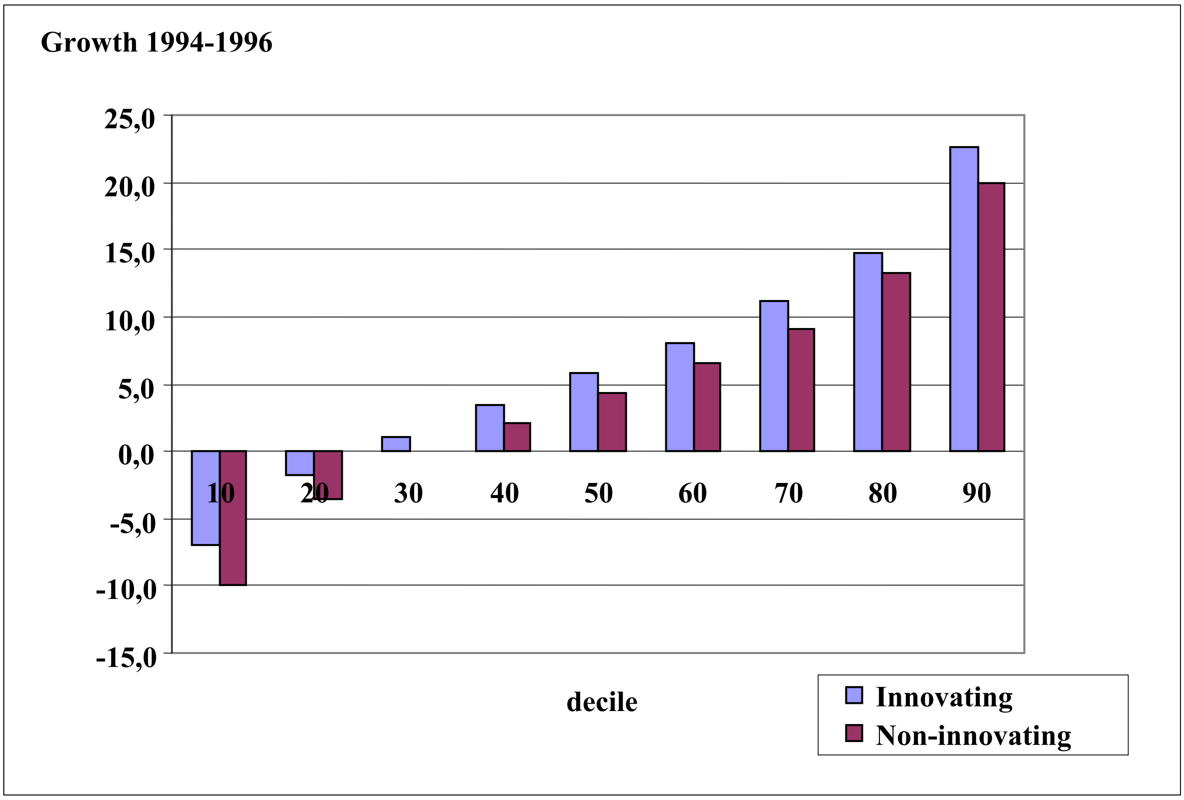
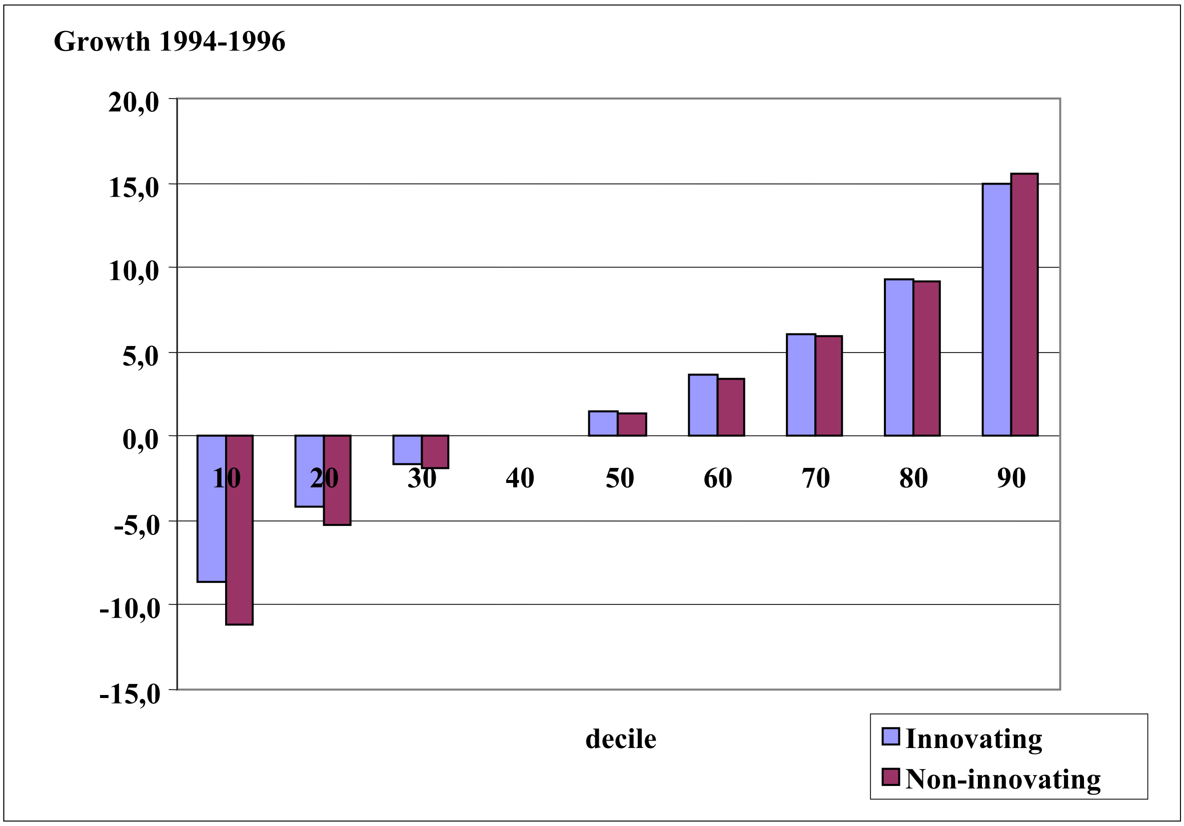


Figure 2.1.b The distribution of employment growth (n = 8328)



2.2.2 A comparison of the performance of innovating and non-innovating firms

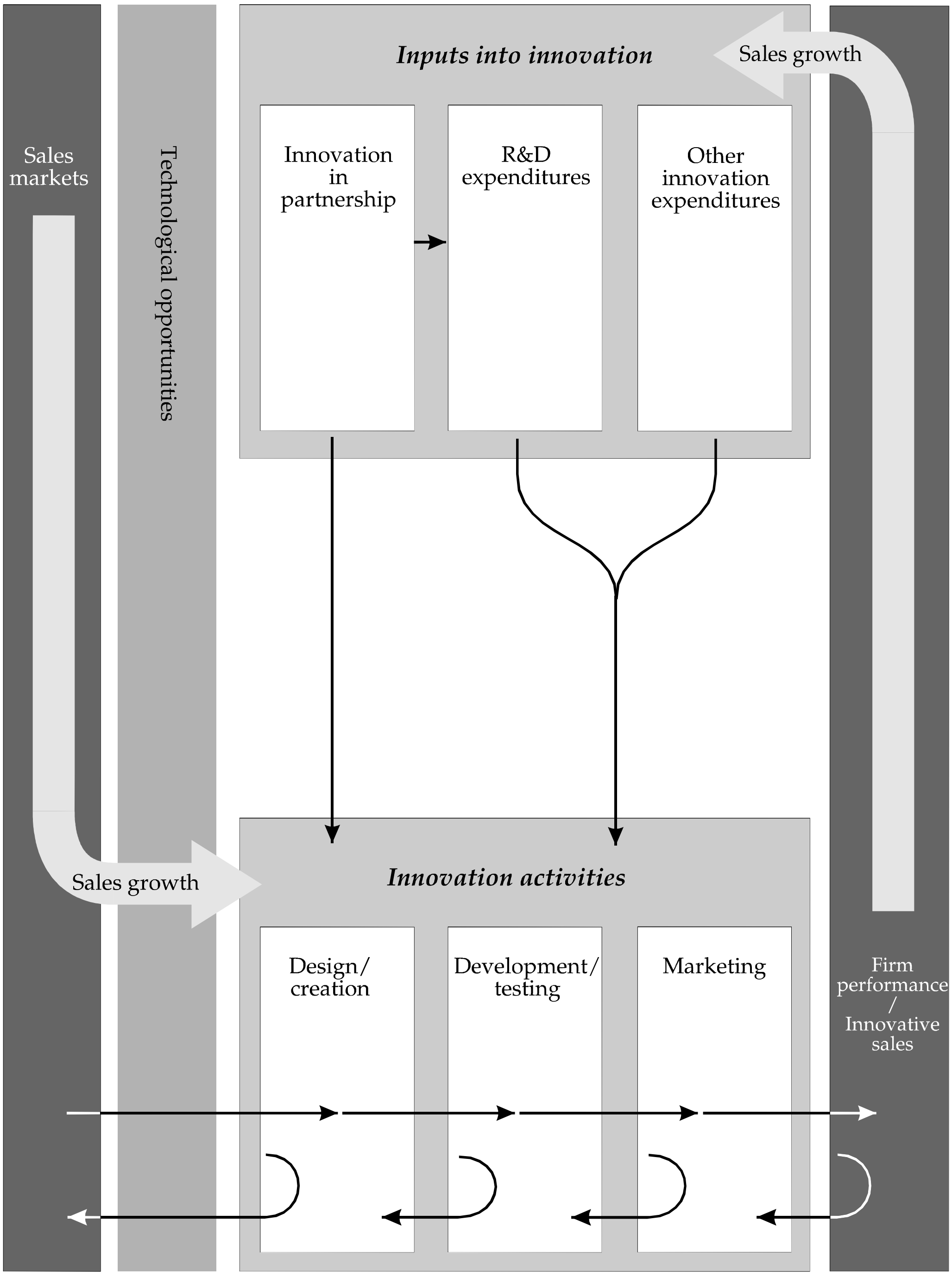
Although the importance of innovation for economic activity is often widely acknowledged, this does not imply that non-innovating firm are performing worse than their innovating counterparts. One can not even exclude the possibility that non-innovating firms perform better on average. Matching the CIS-2 data and the production survey data enables us to compare the performance of innovating and non-innovating firms. A clear picture emerges when we look at the distributions of the two performance measures presented in Figures 2.1a and 2.1b. Evidently, innovating firms were performing better than non-innovating firms with regard to the record of total sales growth but the differences are less pronounced for the growth rates of employment. However, the main message from the distributions presented in these figures is the overwhelming heterogeneity in firm performance for the innovating as well as for the non-innovating firms. Consequently, it is expected that technological innovation will not be able to explain all observable heterogeneity.

2.3 A tentative structural model for the analysis of innovation and economic performance

Using an informal model of the innovation system as a frame of reference and taking into account the data at hand, there are different routes to the empirical testing of the many dimensions underlying the relationship between innovation and overall economic performance. In order to enhance further discussion and as a motivation for the route chosen in this paper, we first present a condensed and adapted summary of the innovation model of Kline and Rosenberg (1986). Figure 2.2 presents some of the main features of their well-known innovation model which we have adopted as a guideline for the specification of the empirical models. The central part of the figure summarises the innovation process and the surrounding bars indicate its positioning within the technological and economic environment.

The two bars at the left side of Figure 2.2 represent a firm's market potential and technological environment respectively. In the empirical application we use the market share in 1994, the growth rate of deflated sector sales for the period 1994 – 1996 (labelled as *SEC*) and dummy variables representing the Pavitt classification of firms to take account of the sector-specific market potentials open to a firm. The technological environment of a firm is represented in the empirical model with the help of different firm-level data. We include two variables which are derived from a factor analysis of the technological opportunities open to the firm by applying a principal component analysis to the data collected on the use of information sources. Following Felder et al. (1996), we use two factors to represent the use of technological opportunities: technological information sourced from ‘science’ and technological information sourced from 'other firms' such as suppliers, customers or competitors. These factors will be denoted by the variables '*SCIENCE*' and '*OTHER*' respectively.[3]

Figure 2.2 The innovation process and firm performance



The technological environment of a firm may also affect its organisational arrangements. In the empirical model we use proxy variables which refer to organisational aspects in order to

[3] The use of publicly available information sources such as journals, scientific literature, fairs and exhibitions is also included in the principal components analysis. These information sources obtain the highest scores for the factor loadings of 'other firms'. Details on the principal components analysis can be found in Klomp and Van Leeuwen (1999).

take account of the notion that a firm may absorb knowledge from the environment via supplier-producer-customer-interactions, or may build up and maintain its own knowledge-base via R&D investment and R&D co-operation. In the empirical model the organisational arrangements will be represented by two dummy variables that indicate the presence of permanent R&D facilities ($D_{R\&D}$) and the emergence of innovation in partnerships with other firms ($D_{co\text{-}op}$) respectively.

The relation between the presence of permanent R&D facilities, 'innovation in partnership' and the two technological opportunity variables ('*SCIENCE*' and '*OTHER*') can be outlined as follows. One may expect a 'cost-push' effect on innovation expenditure of the technological opportunity factor '*SCIENCE*' due to the absorptive capacity argument (see e.g. Cohen and Levinthal, 1989, and Leiponen, 1999). A co-operation between R&D firms and research institutes and universities requires relatively high internal research skills in order to assimilate the fruits of the co-operation and to internalise and commercialise the knowledge created during the co-operation. Contrary, a co-operation with e.g. suppliers, customers and competitors is expected to have lower research competence requirements, a smaller impact on the organisation of firms, and thus a lower 'cost-push' effect on innovation expenditure than the technological opportunity factor '*SCIENCE*'. On the other hand, one can imagine that non-R&D co-operation affects innovation throughput more directly than R&D co-operation and consequently may have a larger effect on the level of innovation output than the technological opportunity factor '*SCIENCE*'.

The central part of Figure 2.2 represents the links within the innovation system itself and the links between a firm's innovation system and its technological environment. Given the market potentials and the technological opportunities open to the firm, the use of technological opportunities may both affect the level of innovation expenditures, as well as the innovation throughput directly. Therefore, the extent of innovation success is expected to depend on investment in innovation, e.g. by building up or maintaining own R&D capital stock or investment in the exploitation of technological opportunities via R&D co-operation, but also on more informal not R&D driven co-operation with other firms.

The upper block of the central part of the figure represents the inputs into innovation. Different routes are open as regards the choice of the measure of the inputs into innovation. CIS-2 uses a rather broad definition of the sources devoted to innovation, with R&D expenditures as the most important component. In spite of the well-known deficiencies of R&D as an indicator for the innovation process, it remains one of the most frequently applied measures (see for instance Kleinknecht (1996) and Kleinknecht and Bain (1993) for a discussion of the deficiencies of the R&D indicator).[4] We could restrict ourselves to R&D expenditures (both intramural and extramural R&D), but doing so we would neglect more than

[4] The availability of time series data for most Western countries seems to be responsible for the frequent use of R&D as a measure for the innovation process. R&D is often the only indicator that allows for international comparison over a time period.

half of all innovation expenditures. Therefore, we use the total of all innovation expenditures components. Following the general practice, a firm's total innovation expenditures is scaled by its total sales and the resulting innovation intensity is used as the measure for the inputs into innovation (labelled as *ININT*).

The lower block represents the well-known functional break-down of the innovation production process (a functional split-up of the innovation activities) which is adopted from the traditional linear innovation model. The interactions between the different innovation activities are indicated with dark arrows. Because we only have data pertaining to the final result of innovation production process, we can not incorporate the underlying activities into the empirical models.

Finally, the bar at the right side of Figure 2.2 represents the feedback links between innovation and overall economic performance. In the empirical application we use the log-odds (labelled as *LOP*) of the share of new or improved products (*P*) to represent the level of innovation output and a firm's total sales ($\Delta logS$) and employment growth ($\Delta logE$) to represent the overall economic performance of firms.[5] Contrary to Klomp and Van Leeuwen (1999) we use deflated turnover as our measure of sales performance.[6] The bar indicates that a firm's innovation output contributes to a firm's total sales growth and thus affects its overall economic performance which in turn is assumed to affect the inputs into innovation. Notice further, that in addition to this link it is also assumed that a firm's overall sales growth may affect the level of innovation output directly.

These feedback links close our tentative model. In a broad view, the model links a firm's own innovation performance to the exogenously given market potentials and to the availability of technological opportunities. Moreover, the model also establishes a framework for the empirical testing of the existence of a persistent relation between its own overall economic performance and its level of innovativeness. The latter will be represented by feedback links running from a firm's own record of sales performance, either to the input stage or to the output stage of the innovation process (or the throughput stage of the complete system if we take a broader view). These feedback loops explicitly acknowledge the dynamic nature of the system.

The proper empirical testing of all lead and lag structures involved ideally would require the availability of longitudinal firm level innovation data. In CIS-2, some longitudinal aspects are present in a crude way, and moreover the longitudinal aspects are restricted to the measures of overall economic performance only. With the available data, the best we can do is to take account of the interdependency of the different stages of the system. Besides establishing a

[5] The choice of the 'log-odds' ratio has been made in order to achieve that the predicted value of the throughput measure lies in between 0 % and 100 %. As a pragmatic solution we imputed a value for *P* of 0.001 respectively 0.999 in order to construct the 'log-odds' ratio for the 315 firms mentioned in subsection 2.2.1.

[6] We used sector price indices for total sales to calculate deflated turnover figures.

framework for the testing of a persistent relation between innovation and economic performance, the model also allows the empirical testing of other hypothesis. With the different variables at hand we can estimate separately equations for the levels of innovation intensity and innovation output. We can also start from the assumption that the inputs into innovation, innovation output and the overall economic performance are jointly determined, and then test e.g. whether technological opportunities and past performance have a separate role in the explanation of differences in innovation output, apart from their impact on innovation expenditures.

2.4 The specification of the empirical model

2.4.1 The structure of the model

From the discussion in the preceding section it follows that a firm's technological environment may affect both its level of innovation intensity (*ININT*) and its level of innovation output (*LOP*) simultaneously. For this reason *ININT* and *LOP* are considered jointly endogenous. The specification of the structure of the simultaneous model is completed by adopting the assumptions that the impact of innovation on a firm's sales growth is channelled mainly through the sales of innovative products and that the feedback links from firm performance to the innovation process may be running to both the input and the output stage (the innovation output) of the innovation process. Furthermore it is assumed that turnover growth may affect employment growth but not the other way around.

According to this reasoning the firm-specific innovation characteristics that are assumed to determine the inputs into innovation and the share of innovative sales should not appear in the equations for a firm's total sales growth ($\Delta logS$) and employment growth ($\Delta logE$). An exception is made for process innovation. With the data at hand the role of process innovation for innovation output and firm performance cannot be taken into account in a very satisfactory way. For many firms the innovation process appears to be directed to product innovation as well as to process innovation simultaneously and the relative importance of both types of innovation cannot be assessed.[7] Process innovation may enhance product innovation (and thus increase the share of innovative sales) but may also lead to increased competitiveness for 'non-innovative' product lines due to reductions of production costs and thus may also affect the overall firm performance more directly. For instance, in Bartelsman et al. (1998) it has been documented that firms that had implemented advanced manufacturing technologies (AMT) showed better performance for employment growth than other firms.

[7] It should be noted further that for 'service firms' no distinction has been made between product and process innovation. Therefore, we can only use this variable for the firms belonging to manufacturing and other sectors.

Given the uncertainty regarding the precise nature of the interaction between product and process innovation and its impact on the overall firm performance it will be assumed that process innovation may have an additional effect on a firm's innovative sales, turnover and employment growth.[8] Summarizing the before mentioned reasoning we keep the specification of the model equations for total turnover growth and employment growth relatively simple. Besides the extent of innovation success, as measured by *LOP*, we include dummy variables to control for industry and size effects and the implementation of process innovation (labelled as $D_{process}$).

2.4.2 The choice of the exogenous variables

The selection of the exogenous variables has been guided by the following considerations. We make a distinction between variables referring to the availability of financial resources (collected in the vector X_1), variables that reflect the organisational aspects of a firm's innovation process and its technological environment (collected in the vector X_2), and other predetermined 'non-innovation' firm-specific variables and industry-specific variables that can be considered as exogenously given to the firm and that will be specified explicitly in the equations.

For many firms the innovation expenditures consist to a large extent of investment components, e.g. expenditures on in-house R&D, licenses and patents and equipment purchased for the implementation of process innovation. We assume that these investment type expenditures are affected by the availability of financial resources and for this reason we take into account two financial variables: the ratio of cash-flow to total sales for 1994 (CF_{1994}) and a dummy variable that refers to the awarding of innovation subsidies (D_{subs}).

The second group of exogenous variables (X_2) consists of the variables already discussed in section 2.3. We use two dummy variables to indicate the presence of permanent R&D facilities ($D_{R\&D}$) and innovation in partnerships ($D_{co\text{-}op}$) and the two continuous variables '*SCIENCE*' and '*OTHER*' derived from a principal components analysis in order to represent the use of technological opportunities. In addition to these variables we also included in the innovation output equation a dummy variable that captures a firm's assessment of the importance of product innovation. This dummy variable (labelled D_{dpull}) takes on a value of one (and zero otherwise) if the replacement of old products or the improvement of the quality of existing products or the extension of market shares and product ranges were rated as (very) important.

The list of exogenous variables is completed by including in the models 'non-innovation' variables that are assumed to be predetermined or exogenous to the firm. Apart from a constant

[8] In the innovation output equation the variable that refers to the implementation of process innovation can be interpreted as a representation of the interaction effect on innovative sales of performing simultaneously product and process innovation.

term we include the logarithm of the age of firms in January 1994 (LA_{1994}) and the logarithm of total sales in 1994 (LS_{1994}) into the innovation input and output equation. This enables us to infer the impact on innovation performance of age conditional on size. Furthermore we include in all equations the growth rate of (deflated) sector sales[9] (*SEC*), a set of dummy variables in order to capture industry-specific effects (*IND*) and a set of dummy variables to represent size effects (*SIZE*).[10]

Then, after appending constant terms, the simultaneous system can be summarized as:

$$ININT = F_1\,(C_1,\ \Delta logS,,\Delta logS,\ SEC,\ X_1\,,\ X_2,,\ LA_{1994}\ ,LS_{1994},,\ IND) \qquad (1A)$$

$$LOP\ \ = F_2\,(C_2,\ ININT,\ \Delta logS,\ SEC,\ X_2\,,\ LA_{1994}\ ,LS_{1994},,IND,\ D_{process}) \qquad (1B)$$

$$\Delta logS = F_3\,(C_3\,,\ LOP,\ SEC,\ IND,\ IND{*}SIZE,\ D_{process}) \qquad (1C)$$

$$\Delta logE = F_4\,(C_4\,,\ LOP,\ \Delta logS\ ,SEC,\ SIZE,\ IND,\ IND{*}SIZE,\ D_{process}) \qquad (1D)$$

where *ININT*, *LOP*, $\Delta logS$ and $\Delta logE$ are the jointly endogenous variables and X_1 and X_2 represent vectors of predetermined financial variables and exogenous explanatory innovation variables that refer to the technological environment of firms respectively.

2.4.3 Selectivity issues

As mentioned in the introduction, we face a special missing variable problem due to the fact that the key variable 'innovation output' has not been measured for the innovating 'service firms'. For this reason the simultaneous model can only be applied using the data of firms belonging to manufacturing and other sectors. It is well known that the manufacturing and service sector showed a rather different performance in the period considered. This can also be verified from some simple descriptive statistics for the variables used in our study. In Appendix 2.1 it can be seen, among others, that the (average) employment growth in the service sector was twice as high as the corresponding figure for manufacturing, a result which indicates that possibility of a selection biases cannot be excluded a priori.

In order to reduce the effects of possible selectivity biases for the estimates of the simultaneous-equations model we incorporated the correction for selectivity in the estimation procedure. Similarly to Lööf and Heshmati (2000) we applied (separately) a generalised Tobit

---

[9] Because of our interest in the feedback from firm performance to innovation we use both the growth rate of own sales *($\Delta logS$)* and the growth rate of market shares ($\Delta logS - SEC$) in the innovation input equation.
[10] For the construction of industry dummy variables, the firms were classified into nine groups of the Pavitt classification and for the 'size' dummy variables we classified the firms into three groups (small, medium sized and large firms). The 'supplier dependent' manufacturing industry and small firms are the reference categories

model and Heckman's two-step procedure for the inputs into innovation as well as innovation output. The methods are explained in Appendix 2.2.

2.5 The estimation results

As mentioned in the foregoing discussion our goal is to analyse the difference of the single-equations and the simultaneous-equations approach. In Tables 2.2 and 2.3 we present the estimates of both approaches for the four endogenous variables of the model, including the results for the selectivity analysis applied to the level of inputs into innovation (*ININT*) and the output the innovation process (*LOP*). The simultaneous model consists of the equations of model (1), after extending the equations for *ININT* and *LOP* with the selectivity variable derived from Heckman's two-step method. The simultaneous model has been estimated with the help of the method of Full Information Maximum Likelihood (FIML). This boils down to assuming that the disturbances of the extended system (1) follow a multivariate normal distribution. Before discussing the various estimates for the different equation we first summarize the results of the selectivity analysis.

2.5.1 Results for the selectivity analysis

The estimates for the Probit step (presented in Appendix 2.3) confirm the empirical fact that – on average – 'business service' firms are younger, performing R&D on a permanent basis less often and have lower market shares compared to manufacturing firms. However, given the market-share of a firm, its probability of 'selection' is negatively related to size (measured by the pre-existing sales level (LS_{1994})). This result indicates that large firms certainly are not overrepresented in the sample of firms for which a measure of innovation output is available. The probability of 'selection' also appears to be negatively related to sector specific growth opportunities (*SEC*), although the corresponding Probit estimates are much smaller then those obtained for the other variables. Finally it can be seen that the estimate of the correlation between the Probit and Tobit part of the system (ρ) are rather small for the two innovation equations (and only weakly significant for *ININT*). This indicates that the effects of selectivity for our data are modest.[11]

2.5.2 The results of the single-equations approach for the innovation equations

Table 2.2 presents the estimates for the two innovation equations: the equations for the inputs into innovation (*ININT*) and the equation for innovation output (as measured by *LOP*). We first discuss the OLS results and OLS plus the Heckman selectivity correction. We use the results of Heckman's two-step method for two reasons. Firstly, Heckman's two-step method is

[11] We recall that the Tobit part of the selectivity model consists of the same variables as used in the simultaneous model.

much easier to integrate with the FIML approach applied for the simultaneous model, and, secondly, the results of Heckman's two-step method were virtually the same as those for the Tobit part of the generalised Tobit model.

Looking first at the results for the OLS estimates for the inputs into innovation, it can be seen that the explanatory variables are significant, with the exception of the estimates of own sales growth (*ΔlogS*) and the dummy variable that refers to innovation in corporation with other partners ($D_{co\text{-}op}$). The results for the simple OLS estimates and the 'selectivity' corrected estimates are virtually the same except for the dummy variable that refers to the presence of permanent R&D ($D_{R\&D}$). Thus, conditional on 'selection', the information that firms perform R&D on a permanent basis does not contribute any more to the observed dispersion in the level of inputs into innovation, because its impact on the level of innovation inputs has been captured by the selectivity variable. This result seems in agreement with Cohen and Klepper's (1996) stylized fact 3.[12]

The explanatory variables that remain most significant, also after the correction for selectivity, are the variables that refer to the use of technological opportunities, the availability of financial resources and size and age respectively. As to the financial variables, we found a significant and positive estimate for the effects of internal cash-flows, but also that the awarding of innovation subsidies contributes significantly and with the expected sign to the inputs into innovation. The estimates of size (LS_{1994}) and age (LA_{1994}) of both the simple OLS estimates and the OLS estimates corrected for selectivity are virtually the same. This indicates that we have decreasing returns to scale to innovation, but also that young firms do have higher innovation intensities than old firms. This result is rather robust as both variables also have been used to model the selection process and because it has also been found in the estimates for the simultaneous model.

Next, we look at the single-equations estimate for the output of the innovation process. The estimation results for the innovation output equation (*LOP*) are presented in lower part of Table 2.2. It is found that performing R&D on a permanent basis ($D_{R\&D}$), the objective 'demand factors considered important' (D_{dpull}) and the use of technological opportunities offered by other firms (*OTHER*) are the variables that are most significant. Notice further, that the effects of performing R&D on a permanent basis on the level of innovation output remains of the same order of magnitude after applying the selectivity correction. This in contrast to the pattern observed for the innovation intensity equation.

[12] Stylized fact 3 of Cohen and Klepper (1996) states that for firms that are engaged in R&D no systematic relation between the level of R&D inputs and size can be observed. Our estimates of Heckman's model indicate that conditional on size there is no effect on the level of innovation intensity of performing R&D on a permanent basis.

Table 2.2 OLS and FIML estimates for equation (1A) and (1B)

	OLS[a]		Heckman[a]		FIML	
	Est.	T[b]	Est.	T[b]	Est.	T[b]
Number of firms	1977		1977		1977	
ININT						
Constant term	14.277	8.8 ***	16.073	8.9 ***	12.490	5.8 ***
CF_{1994}	0.039	3.0 ***	0.039	3.0 ***	0.024	2.6 **
LS_{1994}	-0.840	-7.3 ***	-0.700	-4.8 ***	-0.530	-2.8 ***
$\Delta logS$	0.035	1.4	0.051	1.9 *	0.305	3.2 ***
$\Delta logS - SEC$	-0.051	-2.1 **	-0.067	-2.5 **	0.447	2.6 ***
SCIENCE	0.632	3.9 ***	0.637	3.9 ***	0.480	3.3 ***
OTHER	0.519	3.6 ***	0.529	3.7 ***	0.185	0.9
LA_{1994}	-0.712	-3.1 ***	-0.966	-3.5 ***	-0.608	-4.1 ***
D_{subs}	0.964	3.4 ***	0.937	3.3 ***	1.003	2.8 ***
$D_{R\&D}$	0.783	2.5 **	0.073	0.2	-0.212	-0.3
$D_{co\text{-}op}$	0.480	1.5 *	0.424	1.3	0.053	0.1
Pavitt dummy variables included	yes		yes		yes	
Selection variable			-2.836	-2.4 **	-1.314	-1.0
LOP						
Constant term	-4.504	-6.6 ***	-4.736	-6.4 ***	-6.397	-3.4 ***
ININT	0.031	2.8 ***	0.032	2.9 ***	0.211	1.5 *
LS_{1994}	-0.038	-0.8	-0.056	-1.1	-0.030	-0.3
$\Delta logS$	0.006	1.8 *	0.006	1.8 *	-0.157	-1.1
SEC	-0.004	-0.4	-0.006	-0.6	0.091	1.0
SCIENCE	0.098	1.7 *	0.097	1.7 *	0.017	0.2
OTHER	0.286	4.8 ***	0.285	4.8 ***	0.263	3.1 ***
LA_{1994}	-0.050	-0.7	-0.017	-0.2	0.114	0.8
$D_{R\&D}$	0.974	8.1 ***	1.065	6.3 ***	1.132	4.8 ***
$D_{co\text{-}op}$	0.278	2.3 **	0.285	2.3 **	0.265	1.4
D_{dpull}	1.710	5.9 ***	1.705	5.9 ***	1.571	6.0 ***
$D_{process}$	0.688	5.2 ***	0.689	5.2 ***	0.760	3.5 ***
Pavitt dummy variables included	yes		yes		yes	
Selection variable			0.362	0.8	0.656	1.1
R^2 equation *ININT*	0.100		0.103		0.022	
R^2 equation *LOP*	0.180		0.180		0.063	

[a] T-values are based on heteroscedasticity consistent estimates for the standard errors;
[b] *, ** and *** denote significance at the level of 10, 5 and 1 % respectively.

An interesting result is that the (significant) contribution to innovation output of *SCIENCE* is much lower than the estimated coefficient of *OTHER* indicating that the interactions with customers, suppliers and competitors contribute more directly to innovation output than the use of information from the 'science' sector. However, the latter contributes significantly to the level of inputs into innovation also after applying the correction of selectivity, as can be seen from the upper part of Table 2.2. Furthermore, the results show that the share of innovative sales in total sales does not depend on the size and the age of firms. Thus, conditional on having innovative sales, large (old) firms do not have higher shares of innovative products in total turnover than small (young) firms. This result contradicts stylized fact 4 of Cohen and Klepper (1996), but is in agreement with Lööf and Heshmati (2000) and Crépon et al. (1998).

According to the structure of the model innovation intensities determine the level of innovation output, which in turn are assumed to determine the overall sales performance. In Table 2.2 it can be seen that the single-equations estimate for the innovation intensity in the innovation output equation are rather robust to selectivity but the impact on innovative output is relatively modest. Another interesting result is found for the dummy variable that represents the implementation of process innovation. The impact of process innovation on the level of innovation output appears to be relatively important, indicating that the simultaneous application of product and process innovation enhances innovation output.[13]

2.5.3 Simultaneous-equations estimation

A notable result of the single-equation estimates is that the estimates for the feedback effect from a firm's total sales growth ($\Delta logS$) to the input and the output stage of the innovation process are very modest. For both equations the corresponding estimate of Heckman's model is close to zero. This result can be compared with, for instance Brouwer and Kleinknecht (1999), where it was close to 0.07. This estimate is quite similar to the implied Heckman estimate for the impact of a firm's sectoral demand growth on the inputs into innovation demand growth (*SEC*) of Table 2.2.[14]

These relatively poor results for the testing the Schmookler's demand pull hypothesis (see Schmookler, 1966) may be due to the joint endogeneity of the growth rate of total sales, the innovation-output indicator and the inputs into innovation. Putting it another way, this joint endogeneity calls for a simultaneous-equations approach. The application of a simultaneous model is also motivated by the estimation results of the single-equations approach for some innovation variables. Why does performing R&D on a permanent basis only affect the level of innovation output and not the inputs into innovation? Which are the consequences for 'technological environment' variables for the innovation equations when all interdependencies are taken into account simultaneously? Therefore, we relaxed the implicit exogeneity assumptions underlying the single-equations estimates by assuming that the inputs into innovation, the extent of innovation success and the overall firm performance are jointly determined. After adding disturbance terms to the equations, the system (1A) – (1D) has been estimated with the method of Full Information Maximum Likelihood (FIML).[15]

---

[13] This result is also in agreement with the findings in Lööf and Heshmati (2000). We recall that this estimate should be interpreted as an interaction effect of process innovation on innovative sales.

[14] It should be noted that Brouwer and Kleinknecht (1999) used the growth rate of R&D man years as the dependent variable.

[15] We used the FIML estimation procedure implemented in TSP 4.3.

2.5.3.1 Simultaneous-equations estimates for the innovation equations

The last two columns of Table 2.2 present the simultaneous-equations estimates for the two innovation equations. The results can be compared with the Heckman estimates of the single-equations approach. The most striking difference is that the estimated feedback from overall firm performance to innovation has increased substantially if the interdependencies between the two stages of the innovation process and between the innovation process and overall performance are taken into account more properly. The coefficient of own sales performance rises from 0.05 to 0.30 and, in addition, a significant and positive feedback effect from improving market shares (see the estimated coefficient of $\Delta logS$ - SEC) can be observed. Another notable difference is that the impact of innovation intensities on innovation output rises in the simultaneous model, although the estimate becomes only weakly significant. This result underlines the risk of obtaining a negative simultaneous bias for (gross) 'returns' to innovation output of investment in innovation when using a single-equations approach.

Looking next at the variables that refer to the technological environment of firms, it can be seen that impact of the use of other technological opportunities than those sourced from the 'science sector' no longer contributes significantly to the inputs into innovation, but these opportunities remain a significant determinant of innovation output. On the other hand the impact of the use of technological opportunities sourced from 'science' remains significant and positive in the innovation intensity equation. The latter result may be interpreted as a more robust corroboration of the absorptive capacity hypothesis which conjectures that a co-operation with 'science' requires higher internal R&D skills and thus higher innovation expenditures. The different impact from the environment when using a simultaneous approach also shows up in the estimate for the dummy variable representing a co-operation with other firms ($D_{co\text{-}op}$). When estimating both innovation equations simultaneously, the corresponding estimate turns out to become insignificant in the innovation intensity equation but remains of the same order of magnitude in the innovation output equation (although its significance has been reduced).

In closing the discussion of the estimates for the two innovation equations some brief comments are in order with respect to other variables. The impacts of 'size' and 'age' on the inputs into innovation and the innovation output remain of the same order of magnitude, and also remain insignificant in the innovation output equation. Thus, the results for the tests of stylized facts 3 and 4 of Cohen and Klepper (1996) are preserved in the estimates for the simultaneous model. Finally, there appears to be no feedback effect from the overall firm performance to innovation output, when taking into account the joint endogeneity of innovation output and the overall sales performance.

2.5.3.2 Simultaneous-equations estimates for firm performance

So far, the discussion of the results has been restricted to the equations for the input and output stage of the innovation process only and nothing has been said about the impact of innovation on firm performance, as measured by a firm's growth rate of total turnover and employment growth. We recall that the specifications for the two measures of firm performance are kept relatively simple by assuming that the impact of innovation on firm performance is directed via the impact of innovative sales on total turnover and employment growth, and that, in addition, a

Table 2.3 OLS and FIML estimates for equation (1C) and (1D)

	OLS[a]		FIML	
	Est.	T[b]	Est.	T[b]
Number of firms	1977		1977	
ΔlogS				
Constant term	0.034	0.0	2.710	1.7
LOP	0.352	2.1 **	0.893	2.2 **
$D_{process}$	1.648	1.7 *	1.584	2.0 **
SEC	0.664	6.3 ***	0.665	10.8 ***
Pavitt and size dummy variables included	yes		yes	
ΔlogE				
Constant term	-2.019	-2.5 **	-3.095	-2.4 **
LOP	-0.154	-1.7 *	-0.430	-1.5 *
ΔlogS	0.250	8.7 ***	0.006	0.1
SEC	0.005	0.1	0.168	3.0 ***
$D_{process}$	1.286	2.6 ***	2.183	3.3 ***
Pavitt and size dummy variables included	Yes		yes	
R^2 equation *ΔlogS*	0.070		0.063	
R^2 equation *ΔlogE*	0.183		0.030	

[a] T-values are based on heteroscedasticity consistent estimates for the standard errors;
[b] *, ** and *** denote significance at the level of 10, 5 and 1 % respectively.

firm's performance may be enhanced by the actual implementation of process innovation.[16]

Given these assumptions the discussion of the impacts of innovation on firm performance can be relatively brief. The OLS and the FIML results for the two performance measures are presented in Table 2.3. As expected, the results show a considerable (positive) bias for the single-equations estimate for the coefficient of the sales variable in the employment equation: the estimate for the effects on employment growth of the growth rate of (deflated) total turnover

[16] In contrast to Klomp and Van Leeuwen (1999) we do not use the data on innovation objectives related to process innovation but instead we use the information that firms have actually implemented process innovation.

vanishes when taking into account simultaneity. However, the impact of innovative products on a firm's growth rate of total turnover increases considerably: it is more than doubled if we use a simultaneous-equation model in stead of a single-equations approach. Nevertheless, only a small part of the observed differences in firm performance is explained by the model. This mirrors two things. Firstly, by taking into account all the interdependencies of the whole system, a more significant estimate (in the economic sense) for the impact of innovative sales on the growth rate of total turnover can be obtained, but, secondly, differences in the innovation performances of firms cannot provide more than a partial explanation of the observable heterogeneity in firm performance.

Another interesting result pertains to the contribution of process innovation to firm performance. The estimates indicate that firms who stated to have implemented process innovation show higher turnover growth as well as higher employment growth than other firms. Apparently, implementing process innovation enhances the competitiveness of all sales, and thus a firm's total turnover growth and employment growth. However, the direct impact of innovative sales on employment growth is negative (be it only weakly significant), a results which contradicts the a priori reasoning (and empirical findings of other studies) that the introduction of new and improved products has a positive impact on employment growth.

2.5.4 A comparison with the results of other empirical studies

Our results can be compared with other innovation studies which follow a similar structural approach to the empirical assessment of the importance of innovation for firm performance. Recent examples are presented in Lööf and Heshmati (2000) and Crépon et al. (1998). Contrary to these studies we did not use a production function framework. Consequently, our model is not directed explicitly to an explanation of the impact of innovation on productivity (growth). Furthermore, we use the innovation intensity as an input for the production of innovative output instead of the R&D capital stock. Nevertheless, and notwithstanding these differences, some striking similarities can be observed. Both studies also show that the returns to innovation are higher if one takes into account joint endogeneity of the inputs into innovation, innovative sales and firm performance.

By choosing a firm's total turnover growth and employment growth as the measure of firm performance our study shows more similarities with earlier innovation research, as presented e.g. in Brouwer and Kleinknecht (1994). In these studies a more limited system approach has been followed by linking simultaneously the growth rate of turnover growth and the growth rate for turnover per employee to innovation characteristics. The reduced-form estimates of Brouwer and Kleinknecht (1994) pointed to a (derived) positive effect on employment growth of both product related and process related R&D for the period 1988 – 1990.[17]

With different data, a different observation period and a different model it goes without saying that our results are not very comparable. Our preferred estimates (of the simultaneous-equations model) show a significant and positive effect of innovative sales on turnover growth but not for employment growth. However, our results also indicate that the (derived) effects of innovation on productivity growth are not negligible. The latter result is merely due to the 'direct' impact of process innovation on our performance measures. It can be verified that the implementation of process innovation increases innovative sales as well as (total) turnover growth and employment growth. The last mentioned result seems to be in agreement with Bartelsman et al. (1998). An assessment of the impact of innovation on productivity is – given the structure of the used model – less clear. Nevertheless, it can be seen that difference between the estimates for the coefficient of *LOP* in the equations for turnover and employment growth is about 1.57.[18] Then, taking also into account the 'direct' impact of process innovation on non-innovative sales and employment, one arrives at the conclusion that innovation positively contributes to productivity growth.

2.6 Summary and conclusions

Recent innovation studies place much emphasis on innovation as a production process, with new or improved products as a separate output which enhances the overall firm performance. This enables the linking of a firm's overall sales performance more explicitly to the innovation process, but also calls for empirical methods which are more adapted to new theoretical constructs. This paper presents the results of a micro econometric analysis using the data of the second wave of the Dutch Community Innovation Survey (CIS-2) and methods that take into account the joint dependence of the stages of the innovation process and overall firm performance.

Using the well-known innovation model of Kline and Rosenberg (1986) we have tried to assess the importance of innovation variables for the different stages of the innovation process, the links between innovation and firm performance, as well the existence of feedback effect from a firm's overall performance to its innovation endeavour. This has been achieved by using a four equations model for the inputs into innovation, the probability of innovation success and a firm's total turnover and employment growth. Notwithstanding the limited information in the time dimension of the data we obtain rather plausible and surprising results.

---

[17] Similarly Van Leeuwen and Nieuwenhuijsen (1999) reported a significant impact of product related R&D on employment as well as total turnover. Unfortunately there are no data available in CIS-2 that enables an assessment of the relative importance of both types of innovation.

[18] Using the (co)variances of the corresponding estimates yield a standard error for the difference of 0.8.

Among others, it is found that the impact of the technological environment of a firm on the two stages of the innovation process differs between a single-equations and the simultaneous-equations approach. We found a rather strong evidence for the ‘absorptive-capacity’ hypothesis in the pattern for the estimates pertaining to the use of different technological opportunities. Technological opportunities sourced from ‘science’ are only significant for the explanation of inputs into innovation, but the use of other sources (provided by customers, suppliers or competitors) contribute more directly to innovation output. Furthermore, we found a sizeable impact of performing R&D on a permanent basis on the probability of innovation success and a strong and positive impact of applying process innovation. Our estimates show that, besides enhancing innovation output, the implementation of process innovation also contributes directly to a firm’s overall sales performance and employment growth. In agreement with stylized fact 3 of Cohen and Klepper (1996) we found no impact of ‘permanent’ R&D on the firm’s innovation intensity after conditioning on ‘size’ and ‘age’. However, their stylized fact (4) is rejected in the estimates for ‘size’ and ‘age’ in the innovation output equation: conditional on having innovation output ‘size’ and ‘age’ do not matter any more. Furthermore, our results show that younger firms devote relatively more resources to innovation than large and older firms.

The most notable result is obtained for the links between the innovation process and the overall performance of firms. Similar to Crépon et al. (1998) and Lööf and Heshmati (2000) our estimates underline the benefits of taking into account the joint endogeneity of the key variables of the whole system. Doing this increases both the (gross) returns to innovation output as well as the returns to overall sales performance of inputs into innovation. Taking a shortcut through the preferred estimates it can be seen that innovation contributes significantly to the overall sales performance, productivity (as measured by sales per employee) and employment growth. However, the last result is merely due to the strong and positive impact of process innovation, as the impact of innovative sales on employment growth was found to be negligible. Finally, it can be verified that a more sensible results is obtained for the feedback effect from a firm’s (total) sales performance to its innovation endeavour, when allowing for the joint endogeneity of the innovation process and the overall firm performance: the corresponding simultaneous-equations estimates strongly corroborate Schmookler’s hypothesis.

References

Acs, Z.J., B. Carlsson, and C. Karlsson (eds.), 1999, *Entrepreneurship, Small & Medium-Sized Enterprises and the Macroeconomy*, Cambridge University Press, Cambridge, Mass. USA.

Audretsch, D.B., and R. Thurik (eds.), 1999, *Innovation, Industry Evolution, and Employment*, Cambridge University Press, Cambridge, United Kingdom.

Bartelsman, E.J., G. van Leeuwen and H.R. Nieuwenhuijsen, 1998, “Adoption of Advanced Manufacturing Technology and Firm Performance in the Netherlands”, *The Economics of Innovation and New Technology*, Vol. 6, pp. 291 – 312.

Brouwer, N.M. and A.H. Kleinknecht, 1994, "Technologie, Werkgelegenheid, Winsten en Lonen in Nederlandse bedrijven", OSA-werkdocument W114, Organisatie voor Strategisch Marktonderzoek (OSA), Den Haag.

Brouwer, E., 1997, *Into Innovation, Determinants and Indicators*, Academic Thesis, University of Amsterdam, Elinkwijk B.V., Utrecht.

Brouwer, E. and A. Kleinknecht, 1997, "Determinants of Innovation. A Microeconometric Analysis of Three Alternative Innovation Output Indicators", in E. Brouwer, *Into Innovation, Determinants and Indicators*, Academic Thesis, University of Amsterdam, Elinkwijk B.V., Utrecht.

Brouwer, E. and A. Kleinknecht, 1999, "Keynes-plus ? Effective demand and changes in firm-level R&D: an empirical note", *Cambridge Journal of Economics*, vol. 23, pp. 385 – 391.

Cohen, W.M. and D.A. Levinthal, 1989, "Innovation and Learning: The Two Faces of R&D", *The Economic Journal*, vol. 99, pp. 569 – 596.

Cohen, W.M. and S. Klepper, 1996, "A Reprise of Size and R&D", *The Economic Journal*, vol. 106, pp. 925 – 951.

Cosh, A., A. Hughes and E. Wood, 1998, "Innovation in UK SME's: Causes and Consequences for Firm Failure and Acquisition", in Acs, Z.J., B. Carlsson and C. Karlsson (eds.), *Entrepreneurship, Small and Medium-Sized Enterprises and the Macro-Economy*, Cambridge University Press, Cambridge, Mass., USA.

Crépon, B., E. Duguet and J. Mairesse, 1998, "Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level", *The Economics of Innovation and New Technology*, Vol. 7, pp. 115 – 158.

Felder, J., G. Licht, E. Nerlinger and H. Stahl, 1996, "Factors Determining R&D and Innovation Expenditure", in Kleinknecht, A. (ed.), *Determinants of Innovation, The Message from New Indicators*, Macmillan Press Ltd., London.

Kleinknecht, Alfred (ed.), 1996, *Determinants of Innovation: The Message from New Indicators*, MacMillan Press Ltd., London.

Kleinknecht, Alfred and Donald Bain (eds.), 1993, *New Concepts in Innovation Output Measurement*, St. Martin's Press, Ipswich.

Kline, S.J. and N. Rosenberg, 1986, *An overview of innovation, in Landau, R., and N.Rosenberg, (eds), The Positive Sum Strategy*. Harnessing Technology for Economic Growth, National Academy Press, Washington DC.

Klomp, L. and G. van Leeuwen, 1999, "The importance of innovation for firm performance", Research paper 9936, Department of Statistical Methods, Statistics Netherlands.

Van Leeuwen, G. and H.R. Nieuwenhuijsen, 1999, "Distinguishing between productivity and demand effects of R&D", Research paper 9905, Department of Statistical Methods, Statistics Netherlands.

Leiponen, A., 1999, "Competencies, Collaboration and Innovation", mimeo.

Lööf, H. and H. Heshmati, 2000, "Knowledge Capital and Performance Heterogeneity: A Firm Level Innovation Study", Working Paper Royal Institute of Technology, Stockholm School of Economics, Stockholm.

Maddala, G.S., 1994, *Limited-Dependent and Qualitative Variables in Econometrics*, Econometric Society Monographs No. 3. Cambridge University Press, Cambridge Mass., USA.

Schmookler, J, 1966, *Invention and Economic Growth*, Harvard University Press, Cambridge Mass., Cambridge, USA.

Statistics Netherlands, 1998, *The Knowledge Based Economy 1998*, (in Dutch: Kennis en economie 1998), Voorburg/Heerlen, The Netherlands, December 1998.

Appendix 2.1 Descriptive statistics for the variables used in the models

Variable	Innovating firms (N = 3059)		Firms with innovative output (N = 1977)	
	Mean	SD	Mean	SD
Continous variables				
Endogenous variables:				
• Innovation intensity *(ININT)*	3.295	5.545	3.806	6.105
• Share of innovative sales in total sales (*P*)[a]			0.255	0.253
• 'Log-odds' ratio (*LOP*)			-1.964	2.715
• Annualized growth of deflated sales 1994 – 1996 ($\Delta logS$)	5.410	16.752	4.526	17.573
• Annualized employment growth 1994 – 1996 ($\Delta logE$)	2.152	12.419	0.959	10.480
Exogenous variables:				
• Log Sales 1994 (LS_{1994})	9.786	1.412	9.707	1.378
• Growth rate of deflated sector sales 1994 – 1996 (*SEC*)	6.261	5.463	6.114	6.104
• Cash-flow ratio 1994 (CF_{1994})	12.244	13.411	11.925	13.294
• Technological opportunity 'science' (*SCIENCE*)	-0.002	0.998	0.057	1.039
• Technological opportunity 'other firms' (*OTHER*)	0.013	1.006	0.004	0.991
• Log age in 1994 (LA_{1994})	5.219	0.871	5.288	0.841
• Selectivity variable			0.531	0.199
• Market share in 1994 (MS_{1994})	1.660	5.624	2.136	6.599
Qualitative variables	N		N	
Number of firms with:				
• Innovation subsidies awarded (D_{subs})	1123		936	
• Demand factors considered (very) important (D_{dpull})	2861		1869	
• R&D on a permanent basis ($D_{R\&D}$)	1374		1002	
• Innovation in partnership ($D_{co\text{-}op}$)	874		565	
• Process innovation implemented in 1994 – 1996 ($D_{process}$)	NA[b]		1426	
Firms classified into:				
• Manufacturing 'supplier dependent' (base category)	607		607	
• Chemical industry 'science based' (*Pavitt1*)	249		249	
• Electrotechnical industry 'science based' (*Pavitt2*)	177		177	
• Manufacturing of food 'scale intensive' (*Pavitt3*)	219		219	
• Metal industry 'scale intensive' (*Pavitt4*)	248		248	
• Other industries 'scale intensitive' (*Pavitt5*)	203		203	
• Manufacturing 'specialized supplier' (*Pavitt7*)	274		274	
• Business services 'specialized supplier' (*Pavitt6*)	333			
• Business services 'supplier dominated' (*Pavitt8*)	749			
• Small firms (base category)	1066		720	
• Medium sized firms (*SC1*)	1510		960	
• Large firms (*SC2*)	483		297	

[a] For firms with a percentage share of 0 or 100, a value of 0.001 respectively 0.999 has been imputed;
[b] For 'service firms' no distinction has been made between product and process innovation.

Appendix 2.2 The Methods of Correcting for Selectivity

The methods can be explained using the following two equations:

$$\begin{cases} y_{0i}^{*} = Z_{0i}\beta_0 + \varepsilon_{0i} \\ y_{1i}^{*} \mid y_{0i}^{*} = Z_{1i}\beta_1 + \varepsilon_{1i}. \end{cases} \tag{2}$$

In (2) y_0^* represents a latent (unobserved) variable which describes the probability of being 'selected' and y_1^* the (possibly observed) inputs into innovation (*ININT*) or innovation output (*LOP*). We have $y_0^* = y_0 = 0$ if the data are missing and $y_0^* = y_0 = 1$ if the variables are observed. In the latter case $y_{1i}^* \mid y_{0i}^*$ are replaced by *ININT* or *LOP* respectively. The selectivity bias is expected to be absent, if the errors ε_{0i} and ε_{1i} are not correlated.

In the generalised Tobit model, it is assumed that the disturbances ε_{0i} and ε_{1i} are drawings from a multivariate normal distribution as

$$\begin{pmatrix} \varepsilon_{0i} \\ \varepsilon_{1i} \end{pmatrix} \approx N\left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_0^2 & \rho\sigma_0\sigma_1 \\ \rho\sigma_0\sigma_1 & \sigma_1^2 \end{pmatrix} \right\}. \tag{3}$$

The Generalised Tobit model can be estimated by maximum likelihood after pinpointing σ_0 at unity for identification of the parameters. Heckman's two-step consists of estimating a Probit model for the probability of 'selection' and the OLS estimation of the parameters of the equations for *ININT* and *LOP* after including the Mills's ratio derived from the Probit step. Then, the importance of a selectivity bias can be inferred from the OLS estimate for the coefficient of the Mill's ratio.

The parameters β_0 and β_1 represent the impacts of variables Z_0 on the probability of being observed and the effects on inputs into innovation or innovation output (conditional on being observed) of explanatory variables (Z_1). Because of our intention to purify the estimates of the simultaneous-equations model from (possible) selectivity biases it seems natural to choose for Z_1 the same set of variables as included in the corresponding equations of model (1). Consequently we use in case of the inputs into innovation for Z_1 the explanatory variables of model equation (1A) and for innovation output the explanatory variables of model equation (1B).

For the choice of the variables to be included in different alternatives are available for the variables to be included in Z_0. We use exogeneous variables that reflect some a priori knowledge about the features that are considered typically different for 'service firms' compared to e.g. manufacturing firms. The variables selected for Z_0 refer to the performance of R&D on a permanent basis ($D_{R\&D}$), the market share in total sales in 1994 (labelled as MS_{1994}), the growth rate of deflated sector sales (*SEC*) and the available data on the age of firms and their initial size, measured by LA_{1994} and LS_{1994} respectively. After including a constant term this yields the following composition of the vector Z_0:

$$Z_0 = \{C_0, D_{R\&D}, MS_{94}, LS_{94}, LA_{94}, SEC\}.$$

Appendix 2.3 Results of the Generalised Tobit model

	ININT		***LOP***	
	Est.	T[a]	Est.	T[a]
Number of firms	3059		3059	
Probit part				
Constant term *(C_0)*	1.215	5.2 ***	1.201	5.2 ***
R&D on a permanent basis *($D_{R\&D}$)*	0.487	9.6 ***	0.487	9.6 ***
Market share 1994 (MS_{1994})	0.084	18.8 ***	0.083	18.5 ***
Log Sales 1994 (LS_{1994})	-0.208	-10.9 ***	-0.206	-10.7 ***
Log age in 1994 (LA_{1994})	0.186	7.1 ***	0.185	7.1 ***
Growth rate sector sales 1994 – 1996 (*SEC*)	-0.014	-2.8 ***	-0.014	-2.8 ***
Tobit part				
Constant term	14.770	9.5 ***	-4.624	-6.8 ***
CF_{1994}	0.039	4.5 ***		
D_{subs}	0.958	2.7 ***		
ININT			0.032	3.5 ***
ΔlogS	0.039	1.5 *	0.006	2.1 **
SEC			-0.005	-0.5
ΔlogS - SEC	-0.056	-2.1 **		
LS_{1994}	-0.803	-7.3 ***	-0.047	-0.9
LA_{1994}	-0.781	-5.4 ***	-0.033	-0.4
SCIENCE	0.634	4.9 ***	0.097	1.6 *
OTHER	0.522	3.7 ***	0.285	4.6 ***
$D_{R\&D}$	0.591	1.5 *	1.021	5.8 ***
$D_{co\text{-}op}$	0.465	1.4	0.282	1.9 *
Pavitt dummy variables included				
σ_1^2	5.793	6.8 ***	2.451	75.5 ***
ρ	-0.133	-1.8 *	0.076	0.4
Log Likelihood	-8112.8			-6419.4

[a] *, ** and *** denote significance at the level of 10, 5 and 1 % respectively.

Chapter 3

On the contribution of innovation to multi-factor productivity growth*

Abstract

We embed the innovation production function in a model that analyses the impact of innovation output on multi-factor productivity growth. We combine a market share model with a gross output production function. This revenue approach enables a 'demand-shift' interpretation of the contribution of innovation to multi-factor productivity growth. We apply different sets of instrumental variables and different estimation methods to estimate simultaneously the returns from innovation investment to innovation output, the contribution of innovation output to productivity growth and the feedback link running from a firm's overall sales performance to its innovation endeavour. We draw our empirical results from the second Community Innovation Survey (CIS-2) for the Netherlands. The estimation results from our model show that the impact of innovation differs between measures of firm performance, and that – in our data – the revenue function approach yields more sensible results for the contribution of innovation to multi-factor productivity growth than the value-added production function framework. Furthermore, the results show that the estimation of return on innovation investment benefit from the inclusion of more information on the technological environment of the firm.

3.1 Introduction

A major advantage of innovation surveys over traditional R&D surveys is that they have opened new routes for the assessment of the contribution of innovation to productivity (growth) by enabling an explicit estimation of the innovation production function. According to Griliches (1995), this production function should describe the transformation process that runs from innovation inputs to innovation output. The measurement of a firm's innovation output and the (firm specific) characteristics of the underlying innovation process opens the opportunity for the empirical researcher to disentangle the complex links between innovation and the overall firm performance. By allowing more structure (more equations) and by providing new instruments the new data sources facilitate another step forward in the search of the identification of the contribution of innovation, or more specifically R&D, to productivity (growth) along the lines proposed in Griliches and Mairesse (1997).

Since the data collected in the Community Innovation Surveys have become available, a substantial and still growing body of research has been devoted to the understanding of innovation as a separate process. In a broad sense this strand of research investigates the

---

* This chapter, co-authored by Luuk Klomp, appeared as a Special Issue of *Economics of Innovation and New Technology*, 2006, volume 15 (4/5), pp. 367 – 390. I am thankful to Bert Balk and Gerhard Meinen of Statistics Netherlands, Paul de Boer of the Erasmus University of Rotterdam, the editor and two anonymous referees of 'Economic of Innovation and New Technology', participants of the Workshop on Innovation, Technological Change and Growth in Knowledge-based and Service-intensive Economies, held at Stockholm, February 2001 and participants of the EU Commission Seminar on Innovation and Enterprise Creation, Nice 2000, for their valuable comments and suggestions on earlier versions of this paper and Lieneke Hoeksma for translation assistance.

determinants of innovation strategies and the related decision of how to organise the innovation process in order to capitalise on mutual complementarities between internal and external knowledge bases (see e.g. for recent examples Leiponen (2001), Veugelers (1997) and Veugelers and Cassiman (1999)). By contrast, the newly available data have only been scantly used to disentangle the contribution of innovation to productivity into the return on innovation investment (i.e. the estimation of the innovation production function) and the contribution of innovation output to the overall firm performance. Recent examples of this line of research are presented in Crépon, Duguet and Mairesse (1998), Lööf and Heshmati (2001, this issue) and Klomp and Van Leeuwen (2001).

These studies still differ in many aspects of their empirical setting, in spite of sharing a structural modelling approach to the assessment of the links between innovation and firm performance and the use of the same indicator for innovation output. Differences appear in the choice of the empirical specification for the measures of overall performance and in the way these choices are related to previous research, in the use of data referring to the firm-specific characteristics of the innovation process and in the estimation methods used. Of the three studies mentioned above, Crépon et al. (1998) established a link with previous productivity research by using a value added production function (in levels) to estimate an innovation output elasticity of (total) production.[1] By contrast, the simultaneous linking of innovation output to a firm's employment growth and total sales growth of Klomp and Van Leeuwen (2001) only enables an indirect inference of the contribution of innovation to productivity growth. On the other hand the latter study makes a more extensive use of innovation variables referring to the characteristics of the innovation process itself (the first strand of innovation research mentioned above) than Crépon et al. (1998).

It goes without saying that the results of these different approaches are not directly comparable and that harmonisation of approaches and additional research should be considered. Crépon et al. (1998) mention the use of panel data as an important topic for further research. This would enhance the investigation of dynamics and a better control for unobservable time invariant effects. Controlling for these effects will be possible in the near future if data collection is to be continued in harmonised CIS surveys and if future waves of these surveys remain to be linked to firm-level accounting data.

However, in the mean time, other potential sources of differences require further investigation. The paper has the following contribution to the literature. First, it extends the existing simultaneous models describing the innovation process as well as firm performance.

[1] Contrary to Crépon et al. (1998) the paper of Lööf and Heshmati (2001) also uses other measures of firm performance (e.g. measures related to profitability) which are not taken into account in Klomp and Van Leeuwen (2001).

Our models include a larger set of variables reflecting the innovation process than those used in Crépon et al. (1998) and Lööf and Heshmati (2001). Secondly, the paper sheds light on differences between the approaches applied by Crépon et al. (1998) and Lööf and Heshmati (2001) – hereafter referred to as CDM and LH respectively – and Klomp and Van Leeuwen (2001), hereafter referred to as KL. In our comparison of the various models applied, we show which relations exist between the various approaches. This enhances the interpretation of the different models. Moreover, we conduct a sensitivity analysis using different model specifications and different estimation methods. Among other things our sensitivity analysis will examine the following questions: 1) can we reconcile why KL found a much higher (implied) impact of innovation on labour productivity growth with the lower total factor productivity than that obtained by CDM and LH? 2) to which extent are the different results related to the scope of the simultaneous models and the measures for the inputs into innovation?, and 3) do different estimation methods matter?

Our results show the benefits of including more information on the technological environment of firms for the estimation of return on innovation investment. Furthermore, our model shows that the impact of innovation differs between measures of firm performance and that – in our data – the revenue function approach yields more sensible results for the contribution of innovation to multi-factor productivity growth than the value-added production function framework.

The plan of the paper is as follows. In section 3.2 we outline the specification of the models used in the empirical part of the paper. Section 3.3 summarises the differences and similarities of the various approaches in the literature to embed the knowledge production function in the simultaneous models. Section 3.4 delineates the various alternatives of the benchmark exercise applied in this paper. Section 3.5 discusses the data used in the estimation procedures. The estimation results are presented in section 3.6 and section 3.7 closes with conclusions and a summary of the most important findings.

3.2 A rationalisation of the role of innovation output in a production function framework

A broad view on the various modelling strategies applied to account for the importance of innovation for productivity (growth) is that the different strands of research reflect competing beliefs in the paradigms underlying the explanation of firm performance. At one side of the spectrum we have modelling strategies that fall into the class of (empirical) productivity research based on (adaptations of) the neo-classical theory of production and firm behaviour. In this strand of research – which owes much to Griliches (see e.g. Griliches, 1999) – the production function framework remains the most dominant empirical device. The research of Crépon et al. (1998) and Lööf and Heshmati (2001) are recent examples of an attempt to exploit the newly available innovation data in a production function framework. On the other side of the spectrum we have the less formally based and more indirect investigations of the contribution of innovation to the development of firm performance (for instance measured by productivity or growth in sales or employment). Examples of empirical studies that use the innovation data in this way are given in Brouwer and Kleinknecht (1994), Brouwer (1997), Brouwer and Kleinknecht (1999) and Klomp and Van Leeuwen (2001). In our previous study we analysed the impact of innovation on firm performance with the help of the Dutch innovation survey (CIS2) that covered the years 1994 – 1996. In that study we estimated the impact of innovative sales on the (annualised) growth rates of total sales and employment during 1994 – 1996 simultaneously, thereby obtaining indirectly an estimate of the contribution of innovation to productivity growth (the growth rate of total sales per employee). In this section we summarise well-known material of the standard production function framework and describe a recently proposed modification of this framework to show the relation between the different approaches. Thereafter, we summarise the arguments behind the specification of the equations for the innovation process of our model.

3.2.1 Two alternative specifications of the production function

We start with a production function framework with 'knowledge capital' as a separate input which has been used extensively in empirical applications (see e.g. Mairesse and Sassenou, 1991, and Griliches, 1999 – chapter 4, for an overview). The production function with the inputs physical capital (*C*), labour inputs (*L*), material inputs (*M*) and knowledge capital (*K*) is approximated by a Cobb-Douglas function

$$Q_{it} = AC_{it}^{\alpha} L_{it}^{\beta} M_{it}^{\lambda} K_{it}^{\gamma}, \tag{1}$$

where Q is gross output, A an efficiency parameter (which may be firm-specific) and i and t refer to firms and time respectively. Denoting the logarithms of variables with lower case letters and deleting time subscripts from now on[2], then we can write the corresponding value added productivity equation in terms of value added per employee ($y-l$) as

$$y_i - l_i = a_1 + \alpha_1 (c_i - l_i) + \gamma_1 k_i + (\alpha_1 + \beta_1 - 1) l_i . \tag{2}$$

where α_1 is the elasticity of value added with respect to physical capital and $\alpha_1 + \beta_1 - 1$ measures the deviation from constant returns to scale.[3]

[2] There is no need to distinguish time further because CDM and LH used a cross-section of firm-level data and we use a cross-section of annualised growth rates calculated over the period 1994 – 1996.

[3] For ease of exposition, we do not introduce disturbance terms at this stage. It goes without saying that the different specifications subsequently discussed lead to different interpretations of the disturbance terms.

Another route is to take differences of the logarithmic form of Eq. (1).[4] This yields an expression which relates differences in the growth rates of gross output to the differences in the growth rates of the inputs:

$$\Delta q_i = \alpha \Delta c_i + \beta \Delta l_i + \lambda \Delta m_i + \gamma \Delta k_i . \qquad (3)$$

Using Eq. (3) has the advantage of providing a control for firm-specific fixed effects in the production model, but Eq. (3) or (2) can only be estimated if we have firm-level time-series data for *K*. However, we only used data for total innovation investment in 1996, with R&D expenditures (*R*) as an important component. For this reason we have to reformulate Eq. (3), assuming that gross rates of return to innovation or the marginal product of innovation capital (ρ) are constant across the sample, whereas the elasticities γ vary. Defining $\rho = \partial Q / \partial K$, assuming no depreciation of R&D capital stocks (δ = 0) and using

$$\gamma \Delta k_i = \frac{\rho \Delta K}{Q} = \frac{\rho (R - \delta K_{-1})}{Q} \approx \rho \frac{R}{Q}$$

then the R&D-intensity form of the Cobb-Douglas production function is

$$\Delta q_i = \alpha \Delta c_i + \beta \Delta l \;\; + \lambda \Delta m_i + \rho (\frac{R}{Q})_i . \qquad (4)$$

3.2.2 Modifications of the basic framework

Using the standard production function framework as a starting point, we now describe in more detail the approaches of CDM and LH on one hand and of KL on the other hand. The bottom line in both approaches is that it is not innovation *investment* (or cumulated innovation investment) but innovation *output* that determines the observable differences in productivity (growth). In the case of the CDM model this is implemented rather directly by replacing *k* in (2) with the logarithm of the share of innovative sales in total sales (*ln t*).[5] This yields

$$y_i - l_i = a_2 + \alpha_2 (c_i - l_i) + \gamma_2 \ln t_i + (\alpha_2 + \beta_2 - 1) l_i . \qquad (5)$$

Equation (5) is the expression for (value-added) labour productivity included in their basic model. Notice, that 'returns to scale' are defined relative to the inputs *C* and *L* and that γ_2 thus represents the contribution of knowledge capital to multi-factor productivity (MFP). In fact

[4] As our data on performance measures refers to the years 1994 and 1996 we apply the 'long-difference' form (Δ) instead of 'first difference' (d). Thus, Δ denotes annualised growth.

[5] It should be noted that Crépon et al. (1998) also use another indicator for innovation output, i.e. the number of patents applied. We will not discuss this alternative because this variable is not available in our data.

what is implied by this mutation is that $ln(t)$ captures differences in the level of technological capability and that this variable is endogenous.[6]

It is straightforward to follow the same line of reasoning for Eq. (4), but this would lead to the replacement of the input measure R/Q by the measure of innovation output, i.e. the share of innovative sales in total sales (t)

$$\Delta q_i = \alpha_3 \Delta c_i + \beta_3 \Delta l_i + \lambda_3 \Delta m_i + \rho_3 t_i . \tag{6}$$

In the remainder of this section we elaborate on the specification in Eq. (6) in order to be able to obtain a specification that is adapted to the available data and to establish a link with earlier, comparable studies. What does the coefficient of t measure if we abandon the 'old' practice of using innovation inputs or derived stocks from them and substitute (the share of) innovative sales as a measure of 'knowledge capital'?[7] It seems reasonable to assume that this new variable is more related to market conditions, as innovative sales do not refer directly to 'new' value added by definition. But then, we have to face another problem: the assumption that the impact of innovation on a firm's overall sales performance is channelled through new or improved sales mainly, points to a non-perfect competitive environment by definition. Neglecting that firms operate in an increasingly competitive environment may render theoretical and empirical constructs derived from the assumption of perfect competition inadequately. Klette and Griliches (1996) and Griliches (1999) have shown that this failure may lead to biased estimates for the coefficients of the production function. If knowledge capital is considered to be an input into production, then this implies that the impact of innovation on productivity (growth) may be 'biased'. Firms operating in markets characterised by horizontal product differentiation may possess market power and this makes their relative prices endogenous. The 'solution' of Klette and Griliches (1996) to this problem is to incorporate an equation for market shares and to proceed with a revenue function.

Let the market share equation (in logarithmic form) for firm i operating on market (sector) I be given by

$$q_i^d = q_I + d_i + \eta(p_i - p_I) . \tag{7}$$

In Eq. (7), q_i^d, p_i and q_I denote, respectively, the demand and own price (index) of firm i and total sales of market (sector) I (see section 3.5 for a discussion of the data used in this paper). Furthermore, η represents the demand elasticity with respect to relative prices (or stated otherwise: the 'own' price index relative to the aggregate deflator for market I) and d_i is a

6 Crépon et al. (1998) and Lööf and Heshmati (2001) use the phrase innovation output and 'knowledge capital' interchangeably.

7 We use the share of the share of innovative sales as a measure of 'knowledge capital' in our specifications of the estimated models. Thus, 'knowledge capital' is an output measure in these models, where traditional models usually apply an input measure like R&D capital.

demand-shifter'.[8] Taking into account the definition of deflated total sales or revenues (r_i) given by

$$r_i = (q_i + p_i) - p_I$$

depending on the specification of the 'demand-shifter' in Eq. (7), we can obtain two interpretations for innovative output in the revenue function in 'difference' form.

Let us first assume, in line with CDM, that 'knowledge capital' or (equivalently) the level of technological capability is an input into production. This boils down to assuming that $d_i = 0$. Then, using Eqs. (6) and (7) and taking into account the definition of deflated sales, the revenue function in 'long-difference' form reads

$$\Delta r_i = \varepsilon(\alpha_3 \Delta c_i + \beta_3 \Delta l_i + \lambda_3 \Delta m_i + \rho_3 t_i) - \frac{1}{\eta} \Delta q_I , \tag{8}$$

where the inverse of the mark-up factor is given by $\varepsilon = \dfrac{\eta + 1}{\eta}$.

It can now be verified that Eq. (8) coincides with Eq. (6) only if $\eta \to -\infty$, the case of perfect competition. It can also be seen that imposing the assumption of perfect competition in an invalid way may lead to biased estimates of the production function parameters, including a bias for the parameter which represents the impact of 'technology' on productivity growth.

The opposite approach is to assume that the impacts of innovativeness are directed via their effects on demand conditions. This can be implemented by a parametrization of the 'demand-shifter' with the help of the innovative sales variable. Basically, this approach is similar to Mairesse and Griliches (1984) and Van Leeuwen and Nieuwenhuijsen (1999), who used (the logarithm of) the R&D capital stock for the parametrization of the 'demand-shifter'. However, it is obvious that – taking into consideration the importance of product innovation – a measure of innovative output is more appropriate to capture 'demand shifts' than any measure of inputs into innovation, because it points directly to the final results of innovation. Therefore, we use *t* for the parametrization of the change of the 'demand-shifter' (Δd) in the 'differenced' form of Eq. (7). Thus, we assume that the inter-firm differences in changes of market shares are generated by changes in 'demand-shifts' that are driven by the relative importance of innovative output.

To model the impact of innovation on sales conditions, we remove the term in *t* from Eq. (6) and, using $\Delta d_i = \theta t_i$ in Eq. (7), we then obtain the following alternative specification of the revenue function:

[8] The 'demand-shifter' represents all other effects on demand except price effects.

$$\Delta r_i = \varepsilon(\alpha_3 \Delta c_i + \beta_3 \Delta l_i + \lambda_3 \Delta m_i) - \frac{1}{\eta}\Delta q_I - \frac{\theta}{\eta} t_i . \quad (9)$$

Griliches (1999) pointed out that Eq. (9) reveals what is really estimated when incorporating, under this assumption, an innovation output indicator (t_i) in the production function, namely a shift in demand, attenuated by the price elasticity of demand (η). Nevertheless, there remains an identification problem as we have to assume that the impact of innovation on productivity is a demand effect primarily.

In the empirical application, we try to circumvent this problem by using a dummy variable (D_{proc}) to capture the effects of process innovation on productivity growth.[9] Then, after simple manipulations and adding a constant term to capture the general trend, we can transform Eq. (9) into the following revenue-per-employee growth equation:[10]

$$\begin{aligned}\Delta r_i - \Delta l_i = {} & \mu + \varepsilon\alpha_4(\Delta c_i - \Delta l_i) + \varepsilon\lambda_4(\Delta m_i - \Delta l_i) + \varepsilon(\alpha_4 + \beta_4 + \lambda_4 - 1)\Delta l_i \\ & + \zeta D_{procc} - \frac{1}{\eta}\Delta q_I - \frac{\theta}{\eta} t_i ,\end{aligned} \quad (10)$$

where $\alpha_4 + \beta_4 + \lambda_4 - 1$ measures 'returns to scale' in the traditional production factors: labour inputs, material inputs and physical capital.

Summarising the exposition given earlier, the main differences between our production model and the model of CDM are as follows. Contrary to CDM we use the revenue-per-employee growth as the measure of firm-performance instead of the level of value-added per employee (in logarithmic terms). To our view the applied adaptation of the revenue model is a more appropriate device than the value-added framework of CDM for three reasons. First, our model offers a better framework for assessing the links between the results of the innovation process and firm performance, as the results of the innovation process are measured in revenue terms and not in value-added terms. Secondly, with our model we can also investigate simultaneously the adequacy of the assumption of perfect-competition and the importance of scale economies in the ordinary production factors. Thirdly, the share of innovative sales in total sales is, from a theoretical point of view, a more logical substitute for R&D- or innovation intensities (share of innovation inputs in total sales) than for R&D (innovation) capital stocks.

---

[9] D_{proc} takes on a value of one if a firm actually implemented process innovation in the years 1994 – 1996 and zero otherwise.

[10] Moreover, we include industry and size dummy variables (*IND* and *SIZE*) to control for unobserved industry and size specific effects.

3.2.3 The model for the innovation process

A central part of the various simultaneous approaches consists of a separate modelling of the so-called ‘knowledge production function’ of Griliches (1998). In a broad sense this function describes the transformation process running from inputs into innovation or from innovation investment to innovation output. Innovation surveys provide a direct measurement of innovation output, innovation input and a host of qualitative variables that capture various firm-specific characteristics of the innovation process. However, a generally accepted framework which guides the empirical analysis of all these data is still lacking.[11] Nevertheless, a natural starting point is to regress some measure of innovation output on some measure of (cumulated) innovation investment. Actually this is the basic model for the ‘knowledge production function’ used in CDM. They used data on R&D capital stocks to explain differences in the share of innovative sales in total sales. In their paper they also used an extended model by including indicators capturing whether innovation is driven by ‘demand pull’ or ‘technology push’ factors. Both versions of their model, however, do not pay attention to the organisation of the innovation process at the firm level. However, it is increasingly acknowledged, that the process of knowledge generation at the firm level may be too complex to be captured solely by (the history of) own innovation investment. Measures that refer to (cumulated) innovation investment only, are supposed to provide an incomplete picture of a firm’s own knowledge base. Innovation processes are not purely internal to firms, but may also involve many diverse links with their technological environment, i.e. the so-called external knowledge base.

The interaction between internal and external knowledge bases has been the subject of many studies (see e.g. Cohen and Levinthal, 1989, Lhuillery, 2001, and Marsili, 2001; the last study gives an overview of the micro foundations of knowledge bases). One of the conclusions from these studies is that the technological environment of a firm may also affect its organisational arrangements. Firms may absorb knowledge from the environment via supplier-producer-customer-interactions, or may build up and maintain their own knowledge bases via R&D investment and (R&D) co-operation. The choice between the ‘make’, ‘buy’ or ‘make and buy’ option at the one hand, or between ‘formal’ and ‘informal’ R&D or, more general, innovation at the other hand, may have diverging impacts on the level and composition of innovation expenses. Moreover, utilising the technological environment may also contribute to innovation output more directly. For instance, one can imagine that firms have innovative sales even without spending one dollar on R&D. Therefore, it is expected that innovation expenses only (or

[11] There are various theoretical models which describe the role of innovation for the evolution of firms, but these models do not deliver well defined rules for the empirical testing of the many intricacies at work. See e.g. Klette and Kortum (2001) for a recent attempt to construct theoretical models of industrial evolution that are capable of explaining the observable heterogeneity and dynamics of firm performance and the complexities of the innovation process.

derived input measures from them) do not reveal all intricacies at work.

The innovation surveys contain several variables that refer to the organisation of innovation processes of firms and the interactions with the external knowledge base. We use these variables to model both the inputs into innovation and innovation output simultaneously. We use the variables referring to the objectives underlying the innovation process in the CDM model as a basis. Subsequently, we extend the set of explanatory variables into the direction of the model used in Klomp and Van Leeuwen (2001). We constructed dummy variables, D_{pull1} , D_{pull2} and D_{pull3}, if firms rated the impetus on innovation from demand factors 'weakly', 'moderately' of 'strongly' important respectively ('not important' is the base category).[12] Similarly, we constructed dummy variables D_{push1}, D_{push2} and D_{push3} which represent 'technology push' indicators.[13] This yields a first set of exogenous variables (X_1) which will be included in both equations (see Appendix 3.1 for descriptive measures of the qualitative innovation variables):

$$X_1 = \{D_{pull1}, D_{pull2}, D_{pull3}, D_{push1}, D_{push2}, D_{push3}\}.$$

The technological environment of a firm is represented in the empirical model with the help of different firm-level data. We include two variables which are derived from a factor analysis of the technological opportunities open to the firm by applying a principal components analysis to the data collected on the use of information sources. Following Felder et al. (1996), we use two factors to represent the use of technological opportunities: technological information sourced from 'science' and technological information sourced from 'other firms' such as suppliers, customers or competitors. These factors will be denoted by the variables '*SCIENCE*' and '*OTHER*' respectively.[14] The organisational arrangements will be represented by two dummy variables indicating the presence of permanent R&D facilities ($D_{R\&D}$) and the emergence of innovation in partnerships with other firms ($D_{co\text{-}op}$), respectively.

The relation between the presence of permanent R&D facilities, 'innovation in partnership' and the two technological opportunity variables ('*SCIENCE*' and '*OTHER*') can be outlined as follows. One may expect a 'cost-push' effect on innovation expenditure of the technological opportunity factor '*SCIENCE*' due to the absorptive capacity argument (see e.g. Cohen and Levinthal, 1989). A co-operation between R&D firms and research institutes or universities requires relatively high internal research skills in order to assimilate the fruits of the co-

[12] For the construction of these variables we used the answers to the questions concerning the importance of improving product quality, replacing new for old products and extending existing or creating new product lines.

[13] These variables were derived from the questions concerning innovation objectives which are related to the streamlining of production processes or to economising on the costs of variable inputs.

[14] The use of publicly available information sources such as journals, scientific literature, fairs and exhibitions is also included in the principal components analysis. These information sources obtain the highest scores for the factor loadings of '*OTHER*'. Details on the principal components analysis can be found in Klomp and Van Leeuwen (1999).

operation and to internalise and commercialise the knowledge created during the co-operation. In contrast, R&D co-operation with, for example, suppliers, customers and competitors is expected to have lower research competence requirements, a smaller impact on the organization of firms, and thus a lower 'cost-push' effect on innovation expenditure than the technological opportunity factor '*SCIENCE*'. On the other hand, as mentioned before, informal innovation co-operation may affect innovation output more directly. Collecting these variables yields the second set of exogenous variables (X_2):

$$X_2 = \{SCIENCE, OTHER, D_{co-op}, D_{R\&D}\}.$$

In addition to these 'innovation variables' we also included variables taken from other surveys and business register data in our model. By definition, these are assumed to be predetermined or exogenous to the firm. We include both into the innovation input and output equation the logarithm of the age of firms in January 1994 (LA_{1994}) and the logarithm of employment in 1994 (LE_{1994}).[15] This enables us to infer the impact on innovation performance of age conditional on size and to test whether the stylized facts reported in Cohen and Klepper (1996) also apply to our data. Furthermore we include in both equations the market share of the firm in 1994 (MS_{1994})[16] and the (annualised) growth rate of deflated sectoral sales for the period 1994–1996, already introduced in section 3.2.2 (Δq_I). These variables aim at capturing differences in initial states of competitiveness and exogenously given potentials for sales growth.

The final list of exogenous variables for the modelling of the innovation process consists of financial indicators. For many firms the innovation expenditures consist to a large extent of investment components, e.g. expenditures on in-house R&D, and/or licenses and patents and equipment purchased for the implementation of process innovation. We assume that these investment type expenditures are affected by the availability of financial resources and for this reason we include in the model two financial variables: the ratio of cash-flow to total sales for 1994 (CF_{1994}) and a dummy variable that refers to the awarding of innovation subsidies (D_{subs}). To summarise, we can define three other sets of exogenous variables:[17]

$$X_{3a} = \{MS_{1994}, \Delta\overline{q}_I, LE_{1994}\},\ X_{3b} = \{MS_{1994}, \Delta\overline{q}_I, LA_{1994}, LE_{1994}\} \text{ and } X_4 = \{CF_{1994}, D_{subs}\}.$$

[15] In Klomp and Van Leeuwen (2001) we used the logarithm of total sales in 1994 as a measure of initial size. To be in line with Crépon et al. (1998) we use here employment as the measure of size.

[16] The market share is defined as the turnover of the firm expressed as a percentage of the total turnover in the 3 digit NACE class.

[17] To allow a better comparison with the set of instrumental variables used in the CDM model, a distinction is made between X_{3a} and X_{3b}.

The matrices X_1, X_2, X_3 and X_4 are the building blocks for the construction of the model equations for the innovation process. From the earlier mentioned reasoning, it follows that innovation investment as well as innovation output can be affected by the same factors, although possibly in a different way. Therefore, we assume that the inputs into innovation and innovation output are jointly endogenous. We have no reasons to exclude some of the exogenous variables a priori, except that we do not expect that innovation output will be determined directly by the financial variables contained in X_4. Thus we use the following specifications for the innovation sub-system:

$$I_i = Z_{1i}\pi_{k1} + Z_{2i}\pi_{k2} + \varepsilon_{ki} \tag{11}$$

$$\ln(t_i) = \alpha_k k_i + Z_{1i}\pi_{t1} + \varepsilon_{ti}\ , \tag{12}$$

with $Z_1 = \{X_1, X_2, X_{3b}\}, Z_2 = X_4$. The variable I_i in Eq. (11) represents either the R&D intensity or the innovation intensity (the total of innovation costs as a percentage of total sales) as the measure of innovation inputs, and t_i in Eq. (12) is the share of new and improved sales in total sales.[18] Furthermore, $\pi_{k1}, \pi_{k2}, \pi_{t1}$ are vectors of parameters and ε_{ki} and ε_{ti} are random error terms which are assumed not to be correlated with the exogenous variables. The main parameter of interest is α_k, measuring the impact of innovation investment on innovation output.

3.3 A summary of the differences between the models

Armed with the exposition given in the preceding sections, we now summarise our complete model and discuss the similarities and differences between our model and the CDM model more precisely.[19] The basic feature of our model is that we link two sub-systems, i.e. the model for the innovation process (11) and (12) and the productivity growth Eq. (10) derived from the revenue model. Besides linking innovation output to the overall firm performance we also include backward linkages running from the overall firm performance to the innovation process. This enables us to test Schmookler's (1966) demand pull hypothesis. Then, after adding a firm's total sales growth (Δr) to Eq. (11) and collecting Eqs. (10) – (12), we obtain, after also including disturbance terms, the following system of equations

$$I_i = Z_{1i}\pi_{k1} + Z_{2i}\pi_{k2} + \alpha \Delta r_{i\,r} + \varepsilon_{ki}$$

[18] Similar to CDM we use the logarithmic transformation for the dependent variable of the innovation-output equation.
[19] We do not discuss the model of Lööf and Heshmati (2001) separately, because – in essence – it follows the same structure as the CDM model.

$$\ln(t_i) = \alpha_k I_i + Z_{1i}\pi_{t1} + \varepsilon_{ti}, \tag{13}$$

$$\Delta r_i - \Delta l_i = \mu + \varepsilon\alpha_4(\Delta c_i - \Delta l_i) + \varepsilon\lambda_4(\Delta m_i - \Delta l_i) + \varepsilon(\alpha_4 + \beta_4 + \lambda_4 - 1)\Delta l_i$$

$$+ \zeta D_{procc} - \frac{1}{\eta}\Delta q_I - \frac{\theta}{\eta} t_i + e_{ri}.$$

The parameters α_r, α_k, and $-\theta/\eta$ represent the linkages between the various equations of our system in (13). The estimated parameters represent respectively 1) the backward linkage from a firm's sales performance to innovation inputs, 2) the returns from innovation inputs to innovation output and 3) the impact of innovation output on productivity growth (measured as the growth rate of sales per employee).

Next, we can compare our model with the framework used by CDM. Omitting the constant terms and the error components from their equations, their basic model is given by

$$
\begin{aligned}
g_i^* &= \widetilde{Z}_{oi}\pi_g \\
k_i^* &= \widetilde{Z}_{oi}\pi_k \\
\ln t_i &= \alpha_k k_i^* + \widetilde{Z}_{1i}\pi_t \\
y_i - l_i &= \alpha(c_i - l_i) + \alpha_{ty} \ln t_i + (\alpha + \beta - 1) l_i
\end{aligned}
\tag{14}
$$

The first part of their system (the two equations) consist of a generalised Tobit model used for the estimation of the probability of being engaged in innovation (g^*) and the (latent) inputs into innovation (k^*), which in their application is the (latent) R&D knowledge stock. For the Probit and Tobit part of the model the same set of exogenous variables were used. In their application $\widetilde{Z}_0$ contains data on the size of firms (employment), market shares, diversification,[20] 'demand-pull' and 'technology push' dummy variables, and a set of industry dummy variables. Thus, apart from their diversification index, this is a similar set of exogenous variables as given by X_1 and X_{3a}. The second step in the CDM approach consists of using the estimates of the Tobit part of the generalised Tobit model to construct k_i^* for the estimation of the innovation output equation, the third equation of system (B). In this equation $\widetilde{Z}_1$ contains the same exogenous variables as in $\widetilde{Z}_0$, but with the exclusion of the market share variable. Finally, the predictions from the innovation output equation were used in their productivity equation, which

[20] CDM used the decomposition of sales by 'lines-of-business' to construct an index of diversification.

is equation Eq. (5).

Summarising, we conclude that the main difference between the various approaches concerns the scope of the models, the measurement of firm performance and the use of instrumental variables. In our approach we assume that the firm-specific characteristics of the innovation process may have a diverging impact on the inputs into innovation and innovation output simultaneously. For this reason we use additional instrumental variables to investigate the possible impact of other firm-specific characteristics of innovation processes in addition to innovation or R&D expenses and extend the simultaneous model with an equation for the inputs into innovation. In our research we first look at the selectivity problem for all system equations and thereafter we estimate the whole system simultaneously. In contrast, the CDM approach first 'solves' the possible selectivity problem related to the restricted availability of data on R&D capital stocks, then estimates the return of innovation to these stocks, and finally takes into account the endogeneity of this measure in the productivity equation.

3.3.1 Econometric issues

Another difference between the various approaches concerns the estimation methods used. The preferred estimates of Crépon et al. (1998, CDM) were based on the application of the method of asymptotic least squares[21], those of Lööf and Heshmati on the method of Three-Stages-Least-Squares (3SLS), whereas we used in our previous research the method of Full Information Maximum Likelihood (FIML). The FIML method starts from the rather restrictive assumption that the errors of the system follow a multivariate normal distribution. However, this method is able to account for the constraints linking the parameters of the system. As we do not have cross-equation constraints between parameters and as the 3SLS method assumes no specific distribution of the errors of the system and, moreover, the 3SLS estimates are consistent, we will adopt 3SLS as the preferred method in this paper. This enhances the comparability with the results in the studies by CDM and LH.[22]

The implementation of the estimation method and the identification of the models require that the available instrumental variables are assigned to the endogenous variables of the system. Various candidates for the instrumental variables are already introduced in section 3.2.3. We extend the set of instrumental variables mentioned there with the explanatory variables of the 'performance equation' introduced in section 3.2.2. For instance. for the model that uses Eq. (10), this yields another set of exogenous variables (X_5)

[21] This method is a generalisation of the method of Indirect Least Squares (ILS).

[22] The FIML-estimates are only considered to be better (or at least more efficient) in case of a fully identified model. As we have to do with over-identified models in our study, this requirement is not expected to be fulfilled. Nevertheless, we also applied the FIML-method for some models in order to investigate whether the differences between the estimates of the two methods were statistically significant for our data.

$$X_5 = \{ \Delta c - \Delta l, \Delta m - \Delta l, \Delta l, D_{proc}, IND, SIZE \}.$$

3.4 Delineating the 'benchmark' exercise

In the empirical application we can perform a sensitivity analysis by 'iterating' on different dimensions. We may (1) choose between different measures for innovation inputs and innovation output (2) compare the results of a three-equation system (two equations for the innovation process and one equation for firm performance) with a more limited simultaneous model consisting of equations for innovation-output and firm-performance only, (3) apply different sets of exogenous variables in the estimation method and (4) compare the results of using a simple value-added production function or the revenue function. In order to keep things tractable we have chosen the following route. We start with a comparison of the results for the two-equation system (comparable to system (14) with the results of our model (system (13)). We do so by combining selectivity models (see section 3.6.1) with the estimation of a system consisting of two (three) equations and compare the result of using different sets of exogenous variables. We use two sets of exogenous variables for the simultaneous estimation of the innovation model and the equation for revenue-per-employee growth (10). The first set of instruments consists of the exogenous variables collected in X_1, X_{3a} and X_5.[23] Thereafter, we repeat the same procedure, but now using all available exogenous variables. In all cases we use one measure of innovation output, i.e. the share of innovative sales in total sales, but we shall compare the results for two measures for innovation inputs: the innovation intensity for 1996 (total innovation expenses as a percentage of total sales)[24] and the R&D intensity (total in-house R&D expenditure as a percentage of total sales) for the same year. Finally, and after the sensitivity analysis concerning the specification of the innovation model, we look at the estimates obtained for the alternative measures of firm-performance and starting from the preferred specification of the innovation model.

3.5 The data

As this paper builds on earlier research the data used to estimate our previous models are our reference. The model was applied to the data for 3059 innovating firms, i.e. firms that stated to have implemented product or process innovation during 1994–1996 in some way. After matching the CIS survey with the production surveys it was shown that these firms had higher total sales growth than non-innovating firms but did not show better performance with respect to employment growth on the other hand (see Klomp and Van Leeuwen, 2001, for details). In our

[23] We recall that X_1 and X_{3a} together constitute a similar set of instruments as used by CDM in the reduced-form equations of their innovation model.

[24] When we use innovation intensity in this study, it refers to total innovation expenses as a percentage of total sales and **not** to innovative sales as a percentage of total sales.

previous paper we estimated a simultaneous model for only 1977 of the 3059 innovating firms. This reduction was due to the fact that the key-variable of the model (the share of innovative sales in total sales) was not recorded for firms belonging to the services sector. Firms in services showed (on average) both higher employment and sales growth than manufacturing firms in the period under consideration. The selectivity raised by excluding these firms has been tackled by using a generalised Tobit model.

To estimate our model we need data for the inputs of labour, physical capital, price indices for deflating total sales and material inputs and data on market shares and industry sales (growth). For labour input we use the number of employees reported in the production surveys. The capital input measure required to estimate the models is proxied by the depreciation cost, available in the same surveys. This financial measure is related to the capital stock but does not reflect directly the capital service flow. Tax laws, vintage structures and type distribution of the assets, and cyclical capital utilisation all cause differences between the depreciation data and the desired measure of real capital input. The nominal variables in the data set are deflated by applying industry output (total sales) and material price indices to all firms within the corresponding industry.[25] Furthermore, we constructed market share data for 1994 by linking to the firm-level data the data on total sales at the aggregate (three-digit industry) level for the corresponding year. Finally, we constructed the growth rate of industry sales by deflating the nominal industry sales data at the level corresponding with the available output price indices.

As a consequence of these data manipulations, some additional firms had to be deleted (in particular firms with missing data on their depreciation costs or with a negative score for value-added). Another aspect of the data selection concerns the cleansing of data required to safeguard against undesirable results due to influential observations. In our previous research we did not apply a censoring to the endogenous variables (annualised employment growth and annualised total sales growth), but in this paper we will use the same censoring rules as used in Lööf and Heshmati (2001). Thus, we remove the firms with growth rates for (real) sales per employee and (real) value-added per employee less than -75 % or more than 300%. After this cleansing, our data set reduces to 2985 innovating firms, of which 1926 firms reported innovative output.

Tables 3.1a and 3.1b present some simple descriptive measures for the key variables used in this study for the sample of innovative firms (N = 2985) and the sample of firms used for the estimation of our models (N = 1926) in the period considered.[26] Looking at the median value for the scores, these tables already reveal some interesting aspects of the selectivity problem encountered in our study. The results for the performance measures such as a firm's total sales

[25] The level of detail varies between the two- and three-digit level of the NACE industry classification of firms, with a greater level of detail for output (total sales) price indices than for material price indices.

[26] The growth rates over the period 1994 – 1996 are calculated on an annual basis. See appendix I for the descriptive statistics of the qualitative variables.

Table 3.1a Summary statistics for selected variables innovating firms, N = 2985)

Variable	Median	Q1	Q3	SD
Growth rate of:[1]				
• Employment	1.1	-3.1	6.7	12.4
• Total sales	4.5	-1.9	11.7	15.1
• Value-added	2.3	-5.5	10.7	17.9
• Material inputs	6.9	-1.8	17.0	24.7
• Value added per employee	0.6	-6.5	8.2	16.4
• Sales per employee	2.8	-3.1	9.5	14.0
• Industry sales	5.9	3.8	8.6	5.4
Levels:				
• R&D intensity 1996 (%)	0.2	0.0	1.0	2.5
• Innovation intensity 1996 (%)	1.3	0.4	3.6	5.5
• Market share 1994 (%)	0.3	0.1	1.0	5.6
• Employment in 1994	68	33	135	955
• Employment in 1996	72	35	140	991
• Sales per employee in 1994[2]	103	70	172	470
• Sales per employee in 1996[2]	113	78	181	567
• Value-added per employee in 1994[2]	41	33	54	30
• Value-added per employee in 1996[2]	43	34	56	36

[1] Annualised growth calculated over the period 1994 – 1996.
[2] In 1000 Euro.

Table 3.1b Summary statistics for selected variables (firms with innovative sales, N = 1926)

	Median	Q1	Q3	Std Dev
Growth rate of:[1]				
• Employment	0.0	-3.5	5.2	10.5
• Total sales	3.7	-3.0	11.3	15.2
• Value-added	1.7	-5.8	9.7	17.5
• Material inputs	5.3	-3.7	15.1	23.6
• Value added per employee	1.1	-6.2	8.6	16.1
• Sales per employee	2.9	-3.2	10.2	13.9
• Industry sales	4.9	3.6	9.6	6.0
Levels:				
• R&D intensity 1996 (%)	0.4	0.0	1.3	2.7
• Innovation intensity 1996 (%)	1.7	0.5	4.3	6.1
• Market share 1994 (%)	0.4	0.1	1.4	6.6
• Share of innovative sales in total sales (%)	0.2	0.1	0.4	0.3
• Employment in 1994	67	30	135	922
• Employment in 1996	68	32	135	944
• Sales per employee in 1994[2]	103	75	149	162
• Sales per employee in 1996[2]	115	86	163	168
• Value-added per employee in 1994[2]	41	33	54	26
• Value-added per employee in 1996[2]	44	35	56	29

[1] Annualised growth calculated over the period 1994 – 1996.
[2] In 1000 Euro.

growth and (in particular) its employment growth in the period under consideration, are substantially higher for the business service firms (the firms for which no innovative sales were recorded). It also can be seen that these firms had less inputs into innovation (no matter how it is measured) but, on the other hand, were operating on markets which showed a higher growth potential for their sales performance. Notice further, that this conclusion does not apply to the results for value-added growth in employee terms.

Another striking result concerns material inputs during the period under consideration. For all firms we see (on average) a higher growth rate for material input usage than for (real) sales. We also see that (on average and in both samples) material usage per employee grew much faster than real sales in employee terms. This result points, at least in our data, to an inadequacy of the assumption that materials are used in a fixed proportion of gross output.

3.6 Estimation results

3.6.1 Selectivity issues

We begin the presentation of the empirical results by first looking at the selectivity problem. It should be noted, that our selectivity problem differs from the selectivity encountered by Crépon et al. (1998), where the availability of data on R&D capital stocks has been taken as a starting point for the selectivity analysis. We could follow a similar selection rule here, but we have chosen not to do so, because this may draw too heavily on the role of R&D in explaining differences in innovation output or the overall firm performance. In our data we have no innovative sales recorded for the 'business service' firms and we know that this industry had (on average) a better employment and sales performance than manufacturing in the years 1994 – 1996. For this reason, we investigated whether the impact of the exogenous innovation characteristics, the exogenously given market conditions and the firm's record of overall sales performance (represented by the firm's annualised growth rate of real turnover) on the 'probability of selection' varied between the two industries. Contrary to CDM, we extended the selectivity analysis to all equations of the simultaneous model. To save space we will not comment on the results of all Tobit models applied, but we shall restrict the discussion to the Tobit analysis for the innovation inputs.[27]

The estimates for the Probit part of the corresponding Generalised Tobit model for the two measures of innovation inputs are presented in Appendix 3.2. The results confirm the empirical fact that – on average – 'business service' firms are younger, perform R&D on a permanent basis less frequently and have lower market shares compared to manufacturing firms. The probability of selection also appears to be negatively related to the industry specific growth opportunities (Δq_I), although the corresponding Probit estimates are much smaller than those

[27] Only this part of the selectivity analysis applied in this paper can be compared to the approach of CDM.

obtained for the other variables. Conditional on selection, the level of innovation inputs appears to be negatively related to size (measured by their initial employment (LE_{1994})) and the initial age of the firm (measured by LA_{1994}). These results indicate that large firms certainly are not overrepresented in the sample of firms for which a measure of innovation output is available. It is also interesting to see that the variables referring to the objectives underlying the innovation process have a complete different impact on the Tobit part than on the Probit part of the model. The Probit estimates are significant in most cases, but the Tobit estimates are not. Finally, it can be seen that the estimate of the correlation between the Probit and Tobit part of the system (ρ_{Tobit}) is rather small and insignificant for the two innovation input measures. At first sight this seems to indicate that the effects of selectivity for our data are modest.

The earlier mentioned estimates for the relation between innovation and firm size seem to contradict stylized fact 3 of Cohen and Klepper (1996).[28] However, this result should be interpreted with care, as the Tobit estimates also show that the contribution of the other innovation characteristics differ between the two measures of innovation inputs. Moreover, the Generalised Tobit analysis for innovation inputs does not take into account the joint dependence of the two stages of the innovation process on the innovation characteristics used. Therefore, the estimated relation between innovation (inputs) and firm size may be different when applying the full model. This has been investigated by including 'selectivity correction' variables derived from Heckman's two-step method in all equations of the simultaneous model. Appendix 3.3 (with presents the preferred system estimates for the innovation equations) reveals some evidence on this. There, it is shown that the negative relation between R&D intensities and firm size vanishes when the 'selectivity correction' is applied. This indicates that stylized fact 3 of Cohen and Klepper (1996) is corroborated in our data if we use a simultaneous approach.[29]

3.6.2 Return on innovation investment

In this subsection, our sensitivity analysis concerns the results for the estimated returns from innovation investment to innovation output (α_k) obtained after applying different model specifications. Furthermore, we also look at the consequences of using different sets of instrumental variables.

Let us first compare the results for the return on innovation investment for the alternative models. These are summarised in Table 3.2 for the two input measures. A striking result is that these returns are significantly positive (but small) if we use the single-equation OLS estimates and that these estimates become insignificant (and even negative) in the 'limited system'

[28] Stylized fact 3 of Cohen and Klepper (1996) states that for firms engaged in R&D no systematic relation between the level of R&D inputs and size can be observed.
[29] The latter insignificant estimate for the relation between R&D and firm size is in agreement with the results presented in Crépon et al. (1998).

approach combined with a limited set of instrumental variables. The first mentioned result is not very useful as the OLS results are not valid due to the joint endogeneity of the inputs into innovation and innovation output. In principle this endogeneity problem is taken into account in the system approaches. Table 3.2 also shows that it matters which innovation characteristics are used as instrumental variables for the jointly endogenous variables, in particular if we use R&D intensities as the measure of innovation inputs.

Table 3.2 The impact of innovation inputs (*k*) on innovation output (ln(*t*))[1]

Inputs into innovation	**Innovation intensity (a)**		**R&D intensity (b)**	
	Est.	**SE**	**Est.**	**SE**
a) Limited set of instruments				
OLS	0.041	0.009	0.109	0.040
3-SLS limited system, no selectivity correction[2]	-0.137	0.107	-0.214	0.168
3-SLS full system, no selectivity correction[2]	0.376	0.031	0.678	0.051
3-SLS full system, with selectivity correction[3]	0.466	0.034	0.787	0.053
b) Extended set of instruments				
OLS	0.025	0.008	0.043	0.030
3-SLS limited system, no selectivity correction[2]	0.048	0.056	0.282	0.106
3-SLS full system, no selectivity correction[2]	0.229	0.030	0.515	0.056
3-SLS full system, with selectivity correction[3]	0.297	0.032	0.549	0.057
FIML full system, with selectivity correction[3]	0.242	0.082	0.554	0.195

[1] All estimates represent the return on innovation investment in terms of innovation output and are based on the data of the firms which had innovative sales (N = 1926).
[2] The limited system consists of equations (5c) and (8b); the full system consists of equations (5c), (8a) and (8b).
[3] Selectivity is taken into account by including the inverse of the Mill's ratio as an additional regressor in all equations of the corresponding system.

However, the most striking result is that we obtain the most robust estimates for the return on innovation investment if we take into account the joint dependence of innovation investment as well as innovation output on the innovation characteristics. These results clearly show the combined benefits of using both more 'structure' and more instruments: the estimates of the returns from innovation investment to innovation output increase considerably when the full system is used. Furthermore, it can be noted that this conclusion applies to both measures for innovation inputs.

It is also interesting to see that this conclusion does not change if we correct our estimates for possible selectivity biases, as the results of the models with selectivity correction terms included are not statistically different. The remarkably different results for the return on innovation investment presented in Table 3.2 merit a more detailed discussion of the underlying models for the innovation process. To save space we will only comment on two variants of the model in more detail in Appendix 3.3. It is also interesting to see that the results of the system approaches are not very sensitive to the used estimation procedure. If we adopt the model that uses the full system and all instrumental variables, then the FIML estimates appear to be rather similar to corresponding results of the 3SLS method.

A final comment on Table 3.2 concerns the results for the estimated return on innovation investment if we choose different alternatives for the measure of innovation investment. If we define innovation investment as expenditures on R&D, we have higher return on innovation investment than if we use a 'broader' concept such as the total of innovation expenses. Because we use the same measure for innovation output in both alternatives this is, of course, not a very surprising result.

Table 3.3 3SLS estimates for the parameters of the value-added production functions[1]

Specification	Levels		'Long-differences'	
	Est.	SE	Est.	SE
Number of firms	1389		1389	
A) Specification in levels				
Return on innovation investment[2]	0.742	0.104	0.836	0.107
Physical capital (α)	0.181	0.009	0.056	0.010
Labour (β)	0.888	0.022	0.710	0.048
Share of innovative sales	-0.002	-0.001	0.007	0.056
Returns to scale	0.070	0.019	-0.234	0.047
R^2	0.330		0.085	

[1] All estimates are obtained after using the full system and the extended set of instrumental variables. Selectivity corrections were included in all equations of the full system.
[2] Innovation inputs are measured by the logarithm of R&D per employee in 1996.

3.6.3 The impact of innovation on productivity (growth)

The next step in our analysis concerns the estimates for the two alternative models representing the 'performance' equations of the estimated systems. In this section, we compare the results for the model that uses the value-added production function with the estimates of the productivity-growth model derived from the revenue function approach. We, again, apply two measures of innovation inputs.[30] The equation derived from the revenue model is directly linked to the traditional R&D intensity approach, but instead of innovation inputs as a share of total

[30] We recall that in both models we take into account the endogeneity of the innovative sales indicator and that we have used the logarithmic transformation of the share of innovative sales in total sales as the dependent variable of the innovation output equation and the *untransformed* (same) share as an explanatory variable in the productivity-growth equations.

output (total sales) we now have innovation output as a share of total output (total sales) as an explanatory variable.

We first present – in Table 3.3 – the parameters of the value-added production function in levels (Eq. (5)) as well as for its 'differenced' form (estimated on the basis of annualised growth rates) and obtained after estimating the full system with the help of the complete list of instrumental variables. In addition to the production function parameters we also present estimates for the return on innovation investment, the latter defined (for this model) as the logarithm of R&D expenditures per employee.[31] Our estimates for the return on R&D investment appear to be very significant and also close to those obtained by CDM and LH. However, looking next at the production function parameters, we see insignificant estimates for the impact of innovation output on (multi-factor) productivity (growth), irrespective of the used measure of innovation inputs[32]

This result sharply contrasts the contribution of innovation output to productivity (value-added per employee) of 0.10 found in, for example, CDM. The table also shows the familiar pattern of decreasing production function elasticities and, consequently, a changed interpretation of the scale elasticities, if one changes from the cross-sectional dimension to the time-series dimension of the data. This decrease is more pronounced for capital inputs than for labour inputs and this is probably due to the rather poor measure for the inputs of physical capital used in this study.[33]

Next, we turn to the estimates of the model that uses a productivity growth equation derived from the revenue model (in 'differenced' form). These are presented in Table 3.4. In this variant we have a different measure of multi-factor productivity (MFP) and, consequently, a different interpretation of the contribution of innovation output to MFP.

Beginning with the (traditional) production function elasticities, it can be seen that the two measures of innovation inputs yield very similar and plausible estimates for the elasticities of material inputs as well as for labour inputs. This result carries over to our estimates for the scale elasticities: Table 3.4 shows that the 3SLS estimates indicate significant decreasing returns to scale. These 'scale' estimates seem to be more plausible than the corresponding results obtained for the value-added framework (see the long-difference estimates of Table 3.3). However, it should be noted that the latter results should be taken with care, because the estimate of the capital elasticity remains unsatisfactory low.

[31] This choice enables a comparison with the results of Lööf and Heshmati (2001), who used the same measure of innovation investment in their models. However, this measure of innovation inputs is only comparable to the well-known R&D-capital measure (used also in CDM) in the case of zero R&D depreciation. Furthermore, it should be noted, that this model could be estimated only for the 1389 firms that reported to have R&D expenditures.

[32] We also obtain insignificant coefficients if we use the logarithm of the share of innovative sales in total sales as the innovation output indicator in the two versions of the value-added production function.

[33] For a detailed account of this phenomenon, see Mairesse (1990).

Another notable result concerns the estimates for impact of process innovation on productivity growth. We found a (significantly) negative estimate for this variable. This result may mirror a (possibly) positive impact of innovation on *employment growth*. On the one hand, one can imagine that process innovation reduces employment in the short term. On the other hand, it may affect employment positively in the longer run, as efficiency gains are transmitted to an increased competitiveness on output markets. However, given our models (which assume labour inputs to be exogenous) we cannot address this issue more properly in this study.[34]

Table 3.4 3SLS estimates for the model for revenue-per-employee growth[1]

Innovation inputs	**Innovation intensity**		**R&D intensity**	
	Est.	**SE**	**Est.**	**SE**
Number of firms	1926		1926	
Return on innovation investment	0.297	0.032	0.549	0.057
Constant	-1.383	0.891	-1.443	0.890
Physical capital (α)	0.032	0.005	0.032	0.005
Labour (β)	0.342	0.026	0.346	0.026
Material inputs (λ)	0.52	0.022	0.532	0.022
Innovation output (ϕ)[2]	0.133	0.026	0.132	0.026
Dummy process innovation	-1.256	0.471	-1.028	0.467
Selectivity correction	0.988	1.025	0.945	1.026
'Demand shift' (θ)	1.271	0.530	1.192	0.480
Price elasticity of demand (η)	-9.545	3.289	-9.060	2.962
Inverse of mark-up factor: $(\eta + 1)/\eta$	0.895	0.036	0.890	0.036
Returns to scale	-0.098	0.042	-0.089	0.042
R^2	0.662		0.663	

[1]The estimates are obtained after using the full system and the extended set of instrumental variables; Selectivity corrections were included in all equations of the full system and size and sector dummy variables were included performance equation of the system;
[2] Innovation output is measured as the share of innovative sales in total sales.

Our final observation of the results in Table 3.4 concerns the structural parameters of the underlying demand model. It can be seen that we obtained rather robust estimates for the (inverse) of the mark-up factor. Our results clearly point to a failure of the perfect-competition assumption. Furthermore, the estimates for the 'demand-shift' parameter of the model are rather stable across the two used measures of innovation inputs. The corresponding estimates indicate that if, *ceteris paribus*, the (median) firm increases its share of innovative sales in total sales with 10 percent point (e.g. from 20% to 30%), then, according to our model, the (annualised)

[34] The problem arises – among other things – due to the fact that the majority of the innovative firms in our data stated to have implemented product as well as process innovation simultaneously.

relative growth of its market share will be about 12%.[35] The rather strong impact of innovation output on demand carries over to contribution of innovation to MFP growth. Thus, the productivity-growth model derived from a revenue approach gives much more robust estimates for the impact of innovation on productivity growth, than after using the value-added framework. In our data, the simultaneous estimation of the preferred innovation model and the revenue model leads to an implied estimate of innovation to multi-factor productivity growth of about 0.13.

Summing up, we conclude that we have obtained rather interesting results with respect to the link between innovation and productivity. In the empirical literature it has been often found that the impact of innovation (R&D) on *productivity differences* is more pronounced than the impact of the same variables on *productivity growth,* which were often not significant. The results of Table 3.4 show that the contribution of innovation to productivity in the cross-sectional dimension of the data may be carried over to the time-series dimension of the data after using more elaborate models. Stated otherwise, our results underline the benefits of exploiting innovation surveys for the integration of (more) comprehensive innovation models into a framework for firm performance that is capable of capturing the main features of the links between innovation and firm performance. Finally, we comment on the estimation results concerning the feedback link from firm performance to the input stage of the innovation process. In this paper, the feedback link is represented by the coefficient of Δr in the innovation-input equation. In Appendix 3.3, it is shown that the estimates for the testing of Schmookler's (1966) demand-pull hypothesis point to a positive feedback from total revenue growth (Δr) to innovation inputs (although less significantly if R&D expenditures are taken as the measure of inputs into innovation). It should be noted, however, that the corresponding point estimate is much smaller than that obtained in our previous study (Klomp and van Leeuwen, 2001). This is expected to be due to scope of the model used in this study. In this study we have productivity growth ($\Delta r - \Delta l$) as the single measure of firm performance. In contrast, in our previous study, both total revenue growth (Δr) and employment growth (Δl) were included as the jointly endogenous performance measures in the full model and this may account for the difference when including only Δr, as has been done in this study.

3.7 Summary and conclusions

This paper presents an overview of recent studies on the relation between innovation and firm performance. The exploitation of innovation surveys for the estimation of the so-called knowledge production function and the link between innovation and firm performance (productivity (growth) or growth of turnover or employment) are two common features in these

[35] The median value for the innovation output indicator in our data is approximately 20% and the median market share of firms that had recorded innovative sales is about 0.4%.

studies. The bottom line of the different approaches is that it is not innovation investment but innovation output (measured by the share of innovative sales in total sales) that should be used for the estimation of the contribution of innovation to firm performance (e.g. multi-factor productivity (growth)). This paper raises the question of the interpretation of innovation output in the new modelling approaches. In earlier studies innovation output has been used as a measure of technological capability, thereby abandoning the old practice of using measures of innovation investment or stocks derived from them in the production function framework. This paper suggests an alternative interpretation which – in our opinion – seems to be more adapted to the nature of innovation output.

We use a recently proposed adaptation of the standard production function framework to account for the fact that a firm's innovation output may 'shift' its demand if the firm is operating in a competitive environment. In our empirical application we replace the value-added production function framework used in the other studies by a revenue function approach which combines a gross output production function with a market share model. This enables us to interpret the impact of innovation on productivity growth as a 'demand-shifting' effect. Our baseline model consists of a system that links the innovation process to a single value-added production function or revenue function. The models have been applied to the data of the Dutch Community Innovation Survey (CIS-2) covering the period 1994 – 1996 and production survey data for the same period. We also experimented with different specifications of the exogenous variables for the various endogenous variables of the systems.

Notwithstanding the limited information in the time dimension of the data, we obtain rather plausible results. Among other things, it is found that the return on innovation investment increase if we use information concerning a firm's technological environment in addition to only innovation or R&D intensities. Furthermore, we found that the same innovation characteristics may have different impacts on the input and the output stage of the innovation process. We found rather strong evidence for the 'absorptive-capacity' hypothesis in the pattern for the estimates pertaining to the use of different technological opportunities. Technological opportunities for which 'science' is the source, are only significant for the explanation of inputs into innovation, but the use of other sources (provided by customers, suppliers or competitors) contribute more directly to innovation output. Furthermore, we also found a sizeable impact of performing R&D on a permanent basis on the level of innovation output.

Our estimates for the innovation input equation of the model also show that, conditional on selection, the R&D intensities of firms appear to be invariant to size, which corroborates stylized fact 3 of Cohen and Klepper (1996). However, their stylized fact 4 is rejected for the estimates of 'size' in the innovation output equation: conditional on having innovation output 'size' does not matter, as small firms do not have significant higher innovation output than large firms.

The most robust estimate for the return on innovation investment is obtained when all links between the innovation process and the overall performance of firms are included. Similar to CDM and LH, our estimates underline the benefits of taking into account the joint endogeneity of the key variables of the whole system. However, and in contradiction to the findings in other studies, we do not find a significant impact of innovation output on the level of productivity if we use a value-added productivity equation in our model. By contrast, the use of a revenue function approach appears to yield more sensible results for the contribution of innovation output to productivity growth in terms of the parameters of the underlying market share model. The estimates of the structural parameters of the single-equation revenue function as well as those for the semi-reduced form model point to a significant 'demand-shift' effect of innovation output and a derived multi-factor productivity estimate, which is closer to the results obtained by CDM and LH.

In conclusion, we find two main results. First, when similar model specifications are applied to France (CDM), Sweden (LH) or The Netherlands (this study) rather limited differences are found in the results for the estimated returns – in terms of innovation output – on innovation investment. The exception is that our results for the Netherlands show that the impact of innovation on firm performance, if measured as value-added per employee, is insignificant, which contrasts the results for France and Sweden. On the other hand we obtain a rather sensible result if we use the revenue-per-employee growth as the measure of firm performance. Secondly, the results benefit from the inclusion of additional information on the organisation of the innovation process. In other words, are sensitive to the specification of the model that is applied.

References

Brouwer, N.M. and A.H. Kleinknecht, 1994, Technologie, Werkgelegenheid, Winsten en Lonen in Nederlandse bedrijven, *OSA-werkdocument W114*, Organisatie voor Strategisch Marktonderzoek (OSA), Den Haag.

Brouwer, E., 1997, Into Innovation, Determinants and Indicators, *Academic Thesis, University of Amsterdam*, Elinkwijk B.V., Utrecht.

Brouwer, E. and A. Kleinknecht, 1999, Keynes-plus ? Effective demand and changes in firm-level R&D: an empirical note, *Cambridge Journal of Economics*, vol. 23, pp. 385 – 391.

Cohen, W.M. and D.A. Levinthal, 1989, Innovation and Learning: The Two Faces of R&D*, The Economic Journal*, vol. 99, pp. 569 – 596.

Cohen, W.M. and S. Klepper, 1996, A Reprise of Size and R&D, *The Economic Journal*, vol. 106, pp. 925 – 951.

Crépon, B., E. Duguet and J. Mairesse, 1998, Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level, *The Economics of Innovation and New Technology*, vol. 7, pp. 115 – 158.

Felder, J., G. Licht, E. Nerlinger and H. Stahl, 1996, Factors Determining R&D and Innovation Expenditure, in Kleinknecht, A. (eds.), *Determinants of Innovation, The Message from New Indicators*, Macmillan Press Ltd., London.

Griliches, Z. and J. Mairesse, 1984, Productivity and R&D at the Firm Level, in *R&D, Patents and Productivity*, University of Chicago Press, Chicago.

Griliches, Z., 1998, *R&D and Productivity, The Econometric Evidence*, University of Chicago Press, Chicago.

Griliches, Z., 1999, *R&D, Education, and Productivity, A Retrospective*, Harvard University Press, Boston, USA.

Griliches, Z. and J. Mairesse, 1997, Production Functions: The Search for Identification*, Document de travail CREST 9730*.

Hall, B. H. and J. Mairesse, 1995, Exploring the Relationship between R&D and Productivity in French Manufacturing Firms, *Journal of Econometrics*, vol 65(1), pp. 263 – 293.

Klette, T., J. and Z. Griliches, 1996, The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous, *Journal of Applied Econometrics*, vol. 11, pp. 343 – 361.

Klette, T., J. and S. Kortum, 2001, Innovating Firms: Evidence and Theory, Working paper Presented at: *The Workshop on Innovation, Technological Change and Growth in Knowledge-based and Service-intensive Economies*, Stockholm.

Kline, S.J. and N. Rosenberg, 1986, An overview of innovation, in Landau, R., and N. Rosenberg, (eds), *The Positive Sum Strategy. Harnessing Technology for Economic Growth*, National Academy Press, Washington DC.

Klomp, L. and G. van Leeuwen, 2001, Linking innovation and firm performance: a new approach, *International Journal of the Economics of Business*, vol. 8, pp. 343 – 364.

Van Leeuwen, G. and H.R. Nieuwenhuijsen, 1999, Distinguishing between productivity and demand effects of R&D, *Research paper 9905, Department of Statistical Methods*, Statistics Netherlands.

Leiponen, A., 2001, Organization of Collaboration: An Empirical Analysis of Knowledge Intensive Business Service Relationships, Working paper Presented at: *The Workshop on Innovation, Technological Change and Growth in Knowledge-based and Service-intensive Economies*, Stockholm.

Lhuillery, S., 2001, Innovating Firms: Voluntary technological disclosure as an efficient knowledge management device: an empirical study*,* Working paper Presented at: *The*

Workshop on Innovation, Technological Change and Growth in Knowledge-based and Service-intensive Economies, Stockholm.

Lööf, H. and H. Heshmati, 2001, Knowledge Capital and Performance Heterogeneity: A Firm Level Innovation Study, *International Journal of Production Economics*, forthcoming.

Mairesse, J., 1990, Time-Series and Cross-sectional Estimates on Panel Data: Why Are They Different and Why Should They Be Equal?, in. J. Hartog, G. Ridder and J. Theeuwes (eds.) *Panel Data and Labour Market Studies*, North-Holland, Amsterdam, pp. 81 – 95.

Mairesse, J. and M. Sassenou, 1991, R&D and Productivity: A Survey of Econometric Studies at the Firm Level, *Science – Technology – Industry Review*, OECD, 8. pp. 9 – 43.

Marsili, O, 2001, *The Anatomy and Evolution of Industries*, Edward Elgar Publishing, Northampton, Massachusetts 01060, USA.

Schmookler, J, 1966, *Invention and Economic Growth*, Harvard University Press, Cambridge Mass., Cambridge, USA.

Veugelers, R., 1997, Internal R&D expenditures and external technology sourcing, *Research Policy*, vol. 26, pp. 303 – 315.

Veugelers, R. and B. Cassiman, 1999, Make and buy in innovation strategies: evidence from Belgian Manufacturing firms, *Research Policy*, Vol. 28, pp. 63 – 80.

APPENDIX 3.1 DESCRIPTIVE STATISTICS FOR THE QUALITATIVE VARIABLES

Variable	Innovating firms	Firms with innovative output
	N = 2985	N = 1926
Qualitative variables		
Number of firms with:		
• Innovation subsidies awarded (D_{subs})	1096	979
• Demand factors considered weakly important (D_{dpull1})	297	160
• Demand factors considered moderately important (D_{dpull2})	904	653
• Demand factors considered strongly important (D_{dpull3})	1686	1068
• Technology-push factors considered weakly important (D_{dpush1})	244	155
• Technology-push factors considered moderately important (D_{dpush2})	1200	810
• Technology-push factors considered strongly important (D_{dpush3})	1315	841
• R&D on a permanent basis ($D_{R\&D}$)	1346	979
• Innovation in partnership ($D_{co\text{-}op}$)	852	553
• Process innovation implemented in 1994 – 1996 ($D_{process}$)	NA[1]	1403
Firms classified into:		
• Chemical industry 'science based', NACE 23 - 25 (*Pavitt1*)	246	246
• Electro technical industry 'science based' , NACE 30 - 33 (*Pavitt2*)	165	165
• Manufacturing of food 'scale intensive', NACE 15 - 16 (*Pavitt3*)	218	218
• Metal industry 'scale intensive', NACE 27 - 28 (*Pavitt4*)	245	245
• Other industries 'scale intensive', NACE 10, 11,14, 26, 34, 35, 40, 41 (*Pavitt5*)	196	196
• Manufacturing 'specialized supplier', NACE 32 (*Pavitt7*)	261	261
• Business services 'specialized supplier', NACE 70 -72, 74 (*Pavitt6*)	327	
• Business services 'supplier dominated', NACE 50 - 52, 55, 60 - 67, 90, 93 (*Pavitt8*)	732	
• Manufacturing 'supplier dependent', NACE 17 - 22, 29, 36 - 37 (base category)	595	595
• Small firms (base category)	1039	700
• Medium sized firms (*SC1*)	1472	932
• Large firms (*SC2*)	474	294

[1] For 'service firms' no distinction has been made between product and process innovation.

APPENDIX 3.2 THE GENERALIZED TOBIT MODEL FOR INNOVATION INPUTS

Variable	Innovation intensity			R&D intensity		
	Est.	SE	T	Est.	SE	T
Number of firms	2985			2985		
A) Probit part						
Constant	-0.201	0.239	-0.8	-0.197	0.239	-0.8
MS_{1994}	0.080	0.005	15.6	0.080	0.005	15.7
LE_{1994}	-0.254	0.026	-9.7	-0.254	0.026	-9.7
$\Delta\overline{q}_I$	-0.010	0.006	-1.7	-0.009	0.005	-1.7
D_{pull1}	0.361	0.183	2.0	0.362	0.183	2.0
D_{pull2}	0.448	0.137	3.3	0.448	0.137	3.3
D_{pull3}	0.286	0.138	2.1	0.285	0.138	2.1
D_{push1}	0.152	0.122	1.2	0.151	0.122	1.2
D_{push2}	0.327	0.097	3.4	0.327	0.097	3.4
D_{push3}	0.245	0.099	2.5	0.243	0.099	2.5
$D_{R\&D}$	0.468	0.054	8.7	0.470	0.054	8.7
LA_{1994}	0.166	0.027	6.1	0.165	0.028	6.0
Science	0.087	0.027	3.2	0.087	0.027	3.2
Other	-0.051	0.027	-1.9	-0.051	0.027	-1.9
Δr	-0.005	0.002	-3.2	-0.005	0.002	-3.2
B) Tobit part						
Constant	9.946	2.274	4.4	2.489	1.387	1.8
MS_{1994}	0.056	0.023	2.4	0.035	0.008	4.2
LE_{1994}	-1.059	0.174	-6.1	-0.171	0.063	-2.7
$\Delta\overline{q}_I$	0.024	0.028	0.9	0.015	0.013	1.2
D_{pull1}	-1.470	2.072	-0.7	-0.302	1.475	-0.2
D_{pull2}	-0.091	1.368	-0.1	-0.023	1.128	0.0
D_{pull3}	0.178	1.347	0.1	-0.061	1.130	-0.1
D_{push1}	1.047	0.995	1.1	0.149	0.669	0.2
D_{push2}	0.666	0.885	0.8	0.162	0.591	0.3
D_{push3}	1.063	0.884	1.2	0.133	0.586	0.2
$D_{R\&D}$	0.537	0.497	1.1	1.080	0.264	4.1
LA_{1994}	-0.743	0.176	-4.2	-0.304	0.078	-3.9
Science	0.531	0.145	3.7	0.324	0.053	6.2
Other	0.507	0.160	3.2	0.064	0.080	0.8
D_{SUBS}	0.893	0.346	2.6	0.830	0.235	3.5
CF_{1994}	0.058	0.011	5.4	-0.001	0.005	-0.2
Δr	0.001	0.011	0.1	0.000	0.005	-0.1
σ^2	5.833	0.092	63.3	2.473	0.031	79.4
ρ_{Tobit}	-0.102	0.238	-0.4	-0.104	0.195	-0.5

APPENDIX 3.3 INNOVATION-INPUT AND INNOVATION-OUTPUT EQUATIONS

In this appendix we present the 3SLS estimates for the innovation model underlying the full system. We compare the results for two measures of innovation inputs: the innovation intensity (a) and the R&D intensity (b). An important conclusion is that different innovation characteristics considered have a diverging impact on the various stages of the innovation process. Similar to Klomp and Van Leeuwen (2001), we see a corroboration of the 'absorptive capacity' hypothesis of Cohen and Levinthal (1989) in the estimates of the variables referring to the use of information sources. The use of the technological opportunity '*SCIENCE*' appears to have a significant impact on the inputs into innovation, but not so on innovation output. By contrast, the use of other information sources (e.g. information sourced from customers, clients, competitors seems to have a more direct impact on the level of innovation output than on innovation investment (see the coefficient of the variable '*OTHER*'). Furthermore, and not surprising, our results show that performing R&D on a permanent basis and innovating in partnership both contribute significantly to the level of innovation output.

The results presented here also show some interesting patterns for the contribution of the 'technology push' and 'demand-pull' indicators to the two stages of the innovation process. In the Tobit estimates of Appendix 3.2 model we saw already no significant impact of these variables on the level of the inputs into innovation. This is now confirmed in the estimates for the innovation-input equations. However, it can also be seen that these indicators appear to be very significant for the explanation of differences in innovation output. The pattern and sign of the estimates seems to be consistent with *a priori* beliefs in a sense that estimates of the 'demand-pull' indicators are positive and increasing with their underlying importance ratings. As we also obtained less significant estimates for the 'technology push' indicators, these results clearly underline that innovation is a demand driven process predominantly.

The results presented in this appendix enable a more accurate verification of the stylized facts of Cohen and Klepper (1996). If we take the results of the extended model as our preferred results, then their stylized fact 3, referring to the positive relation between R&D investment and firm size, seems to be corroborated in our estimates. Furthermore, our estimates also show no significant relation between innovation output and size in our preferred model. This contrasts stylized fact 4 of Cohen and Klepper (1996).

Finally, we comment on the estimation results for the two stages of the innovation process concerning the estimated feedback link from the overall sales performance to the input stage of the innovation process, represented by the coefficient of Δr in the innovation-input equation. The estimates for testing Schmookler's (1966) demand-pull hypothesis show that we have a significant positive feedback from revenue growth on innovation inputs, but the estimate is less significant if we use the R&D intensity as the measure of inputs into innovation.

Estimation results for the innovation input and innovation output equations

Variable	Innovation intensity (a)			R&D intensity (b)		
	Est.	SE	T	Est.	SE	T
Number of firms	1926			1926		
A) Input equation						
Constant	13.758	2.348	5.9	3.673	1.005	3.7
MS_{1994}	-0.004	0.036	-0.1	0.015	0.015	0.9
LE_{1994}	-0.634	0.233	-2.7	-0.033	0.100	-0.3
$\Delta\bar{q}_I$	0.028	0.024	1.2	0.018	0.010	1.7
D_{pull1}	-2.289	1.222	-1.9	-0.548	0.519	-1.1
D_{pull2}	-1.072	1.017	-1.1	-0.321	0.433	-0.7
D_{pull3}	-0.494	0.971	-0.5	-0.263	0.413	-0.6
D_{push1}	0.832	0.733	1.1	0.071	0.311	0.2
D_{push2}	0.079	0.661	0.1	-0.032	0.281	-0.1
D_{push3}	0.627	0.640	1.0	-0.010	0.272	0.0
$D_{R\&D}$	-0.431	0.533	-0.8	0.795	0.228	3.5
LA_{1994}	-1.042	0.226	-4.6	-0.405	0.097	-4.2
Science	0.374	0.158	2.4	0.276	0.067	4.1
Other	0.608	0.156	3.9	0.093	0.066	1.4
D_{SUBS}	1.008	0.281	3.6	0.786	0.123	6.4
CF_{1994}	0.024	0.012	2.0	-0.006	0.005	-1.2
Δr	0.025	0.010	2.5	0.008	0.004	1.8
Selectivity correction	-4.293	1.802	-2.4	-1.445	0.776	-1.9
Pseudo R^2	0.082			0.162		
B) Output equation						
Innovation inputs	0.297	0.032	9.4	0.549	0.057	9.6
Constant	-9.606	0.782	-12.3	-7.896	0.683	-11.6
LE_{1994}	0.019	0.057	0.3	-0.202	0.052	-3.9
$\Delta\bar{q}_I$	-0.010	0.008	-1.1	-0.014	0.008	-1.7
D_{pull1}	2.033	0.425	4.8	1.734	0.411	4.2
D_{pull2}	2.619	0.339	7.7	2.554	0.330	7.7
D_{pull3}	2.779	0.334	8.3	2.829	0.326	8.7
D_{push1}	-0.279	0.259	-1.1	-0.028	0.252	-0.1
D_{push2}	-0.153	0.217	-0.7	-0.029	0.212	-0.1
D_{push3}	-0.511	0.218	-2.3	-0.259	0.212	-1.2
$D_{R\&D}$	1.200	0.137	8.7	0.699	0.145	4.8
LA_{1994}	0.370	0.071	5.2	0.330	0.067	4.9
Science	0.032	0.054	0.6	0.007	0.053	0.1
Other	0.046	0.057	0.8	0.166	0.053	3.1
$D_{co\text{-}op}$	0.182	0.103	1.8	0.204	0.102	2.0
Selectivity correction	2.073	0.383	5.4	2.033	0.373	5.4
Pseudo R^2	0.071			0.083		

[1] The (3SLS) estimates are obtained after using the full system and all instrumental variables.

Chapter 4

Linking innovation to productivity growth using two waves of the Community Innovation Survey (CIS)*

Abstract

Using two waves of the Community Innovation Survey for the Netherlands we integrate recent lines of research to estimate the contribution of innovation to manufacturing multi-factor productivity (MFP) growth. The model uses CIS data to control for the complementarity between internal and external knowledge bases and also investigates the importance of within-firm time interdependencies for inputs into innovation and innovation output. Our results show the benefits of including more information on the technological environment of firms. Furthermore, the model shows that tracking the innovation performance of firm over time leads to a lower persistence of innovativeness when measured from the output side than when measured from the input side through use of R&D. Moreover, the contribution of innovation to MFP increases when estimating a static innovation model that uses the data obtained after pooling the two waves of CIS. The latter result reflects the difficulty of accounting properly for the non-rivalry of innovation and the associated inter-firm 'spillovers' of knowledge creation when using firm-panel data alone.

4.1 Introduction

About ten years ago that the OECD took the initiative of setting up guidelines for the formulation and the design of innovation surveys. Since the emergence of the Oslo Manual (OECD, 1992) a number of countries have launched at least two surveys, known as Community Innovation Surveys (CIS). In contrast to other countries, and prior to the third wave of the big and harmonised European CIS3 survey which is now underway, Statistics Netherlands has carried out an intervening survey (called CIS2,5) on the basis of a panel design. This paper presents the results of a first attempt to make use of two similar innovation surveys (CIS2 and CIS2,5) and the production surveys for the same reporting units to construct a panel for both innovation variables and performance measures.[1] To our knowledge this is the first example of the use of panel data for innovation variables to investigate a number of theoretical issues raised over the past decade.

Innovation surveys emerged from a growing concern about the following deficiencies of the traditional R&D surveys: 1) inputs into innovation were insufficiently covered by R&D

* This chapter was published as STI working paper 2002/8, OECD Directorate for Science, Technology and Industry, Paris. A first version of this paper was presented at the OECD Workshop on Firm-level Statistics, Paris, 26-27 November 2001. The author would like to thank Bert Balk for his valuable comments.

[1] In the Netherlands, CIS1 (covering 1992–1994) and CIS2 (covering 1994–1996) were conducted by different institutions. As a consequence of the use of different sampling frames, it appeared to be impossible to link these surveys at the micro level and to use the linked data for analysing the dynamics of innovation. Another difference between the two surveys concerns the questions asked and the reporting unit. From CIS2 onwards, the CIS surveys are considered to be harmonised and are conducted in more or less the same fashion.

expenditures alone, 2) appropriate and direct measures of the output of the innovation process were lacking, indirect measures such as patent applications were considered insufficient, and 3) data on the organisation of innovation process and the importance of knowledge flows between firms were required.

It is clear that CIS has opened new routes for the assessment of the contribution of innovation to productivity (growth). First, the use of a direct measurement of a firm's innovation output enables an explicit estimation of the innovation production function (see e.g. Griliches, 1998). In addition, the data on the (firm specific) characteristics of the innovation process permit a more direct analysis of the importance of knowledge flows between firms or between firms and other organisations, both for building up and maintaining internal knowledge bases or for the output of the innovation process. Second, if direct measures of innovation output are available, some of the disadvantages of the widely used knowledge-capital-stock approach can be circumvented. Third, embedding the innovation production function in a structural model enables a better understanding of the complex links between innovation and productivity growth. By allowing greater structure (more equations) and by providing new instruments, the new data sources are a step forward in the search for the identification of the contribution of innovation, or more specifically R&D, to productivity growth along the lines proposed in Griliches and Mairesse (1997).

Since the harmonised CIS data have become available, only relatively few studies have tried to use the new data for the purpose of estimating the contribution of innovation to firm performance. Recent examples are presented in Crépon et al. (1998), Lööf and Heshmati (2001) and Klomp and Van Leeuwen (2001a). All these studies could make use of only one wave of CIS. In the present paper previous cross-sectional analysis by Klomp and Van Leeuwen (2001) is extended using the two waves of CIS to incorporate recent lines of research in a structural modelling approach. Adaptations of the model for knowledge-stock accumulation suggested by, among others, Hall and Hayashi (1989) and Klette (1996) and the revenue approach of Klette and Griliches (1996) are used to embed the innovation process in a model that aims to explain differences in productivity growth. The model simultaneously takes into account the importance of innovation for the competitive environment of firms and uses the innovation panel to investigate the within-firm time interdependencies of innovation output and the importance of inter-firm knowledge flows.

The model adaptations yield a dynamic system for the innovation process which, on the one hand, may present a better description of the intricacies at work, but, on the other hand, also introduce a myriad of other problems. The first results show that many firms that innovated in CIS2 were absent in CIS2,5. Nevertheless, the coverage of innovating firms was very similar in the two surveys. This loss of data severely complicates the use of a dynamic innovation model, as it may be due to discontinuities of the innovation process itself (e.g. triggered by the depletion of technological opportunities). In the estimation procedure I have tried as far as possible to control for this source of endogenous attrition. Furthermore, the results obtained using the dynamic innovation equations in the full model are compared with those from implementing a static version of the innovation model that can be applied to a more extensive data set.

The plan of the paper is as follows. In sections 4.2 and 4.3 I discuss the derivation of the dynamic innovation model and the linking of this model to our model for productivity growth. Section 4.4 discusses the construction of the data. In this section some descriptive measures that enable a comparison of the performance of innovating and non-innovating firms are presented. The estimation results for the various models are presented in section 4.5. Section 4.6 summarises and concludes.

4.2 The relation with previous research

4.2.1 Adaptations of the basic framework

In this section some adaptations of the basic framework proposed in recent literature are outlined (see Appendix 4.1 for a summary of this framework). These adaptations concern 1) modification of the model for the process of knowledge accumulation underlying the R&D production function framework and 2) extension of the traditional reduced-form R&D models into the direction of a structural model as an attempt to exploit the CIS data. The first strand of research (which is the subject of subsection 4.2.1) discusses the separability of current R&D efforts and the internal knowledge base previously acquired. The second strand of research (discussed in subsection 4.2.2) models innovation as a separate process and discusses how this process can be linked to the overall firm performance. A link is established between the two strands of research by combining a (reduced-form) revenue model and a dynamic model for the innovation process.

4.2.2 The process of knowledge accumulation

Many discussions concerning the traditional R&D-productivity framework are centred around the concept of knowledge production and how the usually applied procedure of constructing R&D-capital stocks fits into this concept. The disadvantages of using the capital-accumulation equation for firm I ($I = 1, \dots, N$) in year t ($t = 1996, 1998$):

$$K_{it} = (1-\delta)K_{it-1} + R_{it} \tag{1}$$

as a model for knowledge production has been discussed extensively in the literature (see e.g. Griliches, 1998). In this framework, K is a measure of knowledge stocks and R a measure of R&D or innovation investment. In this paper the focus is on the central point of criticism which concerns the separability of current R&D efforts and the level of innovativeness already achieved.

As the equation is homogeneous of degree one in current R&D, Equation (1) implies constant returns of R&D to knowledge production. Thus (1) neglects any complementarity between current R&D and the knowledge already captured in the existing stock or the history of R&D investment. Griliches (1998) has been pointed out that the process of knowledge production of firms induced by their own R&D history may be different in this respect from other capital investment. A firm's R&D investment may depend in a non-linear fashion not only on its current own R&D but also on (own) previously accumulated results derived from R&D and – moreover – also on the absorption of knowledge sourced from its technological environment.

An alternative specification provided by e.g. Hall and Hayashi (1989) and Klettte (1996) gets to the core of this criticism and is given by:

$$K_{it} = K_{it-1}^{\rho-\upsilon} R_{it-1}^{\upsilon}, \tag{2a}$$

From Equation (2a) it can be derived that the marginal product of R&D is inversely related to the current R&D effort, which implies decreasing returns of R&D to knowledge capital.[2] Klette (1996) rationalises (2a) as follows: "… the complementarity in knowledge production may explain why firms with a high rate of *return to knowledge capital* may have little incentive to carry out R&D because they may have too little knowledge capital or too few R&D skills to get much knowledge out of its new R&D investment. Similarly, firms with a low rate of *return to knowledge capital* might prefer to carry out more R&D as the knowledge capital already acquired makes the current R&D effort more productive …".

Taking logarithms of the variables and adding a constant term, equation (2a) can be transformed into:

$$k_{it} = \mu_3 + \theta_1 k_{it-1} + \theta_2 r_{it-1} \tag{2b}$$

The parameters of interest in (2b) are θ_1 and θ_2. If θ_1 is larger (smaller) than one, then we have increasing (decreasing) returns in the knowledge production function. The estimate of θ_2 represents the innovation opportunities of R&D. The estimate of θ_1 can be considered as a measure of the persistence of the knowledge capital already acquired. A high value signals significant scale economies in R&D. An estimate larger than one points to a cumulative process,

[2] Equation (2a) has the undesirable property that knowledge capital vanishes if R&D expenditure is zero. This problem can be taken into account in the estimation procedure by imputing one (guilder) for R&D and using a 'No-R&D' dummy variable in the regression model.

whereby an above-average firm departs more and more from the average firm, even if its R&D efforts are average.[3] By contrast, a low value of θ_1 signals a low persistence of knowledge capital. This may be due to the depletion of technological opportunities as a result of (unintended) spillovers and diffusion of knowledge to competitors. In this case, there is a tendency to convergence, as a firm with an above average knowledge capital gravitates down towards to the average firm, even if it carries out the average amount of R&D.

The usual procedure to implement (2b) in the empirical model is to find some way to solve out the unobservable *k.* Klette (1996) achieved this by combining a demand model with an equation for *productivity differences* relative to the reference firm (represented by the average over all firms). The empirical model finally obtained is a dynamic equation in *Solow-residual productivity differences* with the contribution of innovation represented by (the logarithm of) lagged R&D. Thus in essence this remains a (modified) reduced-form R&D model. Besides the drawback that these types of models remain based on measures of inputs into innovation,[4] they also suffer from the disadvantage that the importance of knowledge flows between firms is not taken into account.

4.2.3 Structural modelling approaches

It is at this stage that the CIS data come into play. The main feature of CIS is that the survey is directed at the innovation process itself. The CIS surveys aim to describe the innovation process by collecting data on the inputs into innovation (innovation investment disaggregated by type), innovation output (measured by the share of new or improved sales in total sales), and data to describe the technological environment of firms and the importance of inter-firm knowledge flows.

One of the new variables collected, and which seems to be most promising in view of the problems encountered in previous research, concerns the direct measurement of innovation output, represented by the share of new and of improved sales in total sales. It seems straightforward to use this variable and data on the firm-specific characteristics of the innovation process for the estimation of a (enhanced) knowledge production function as an alternative for (2b).

Unfortunately, this new comes has a price. A first problem to note is that innovation output should be linked to the overall firm performance in some way, in order to enable an assessment of the contribution of innovation to productivity (growth). The change from input to output

[3] This interpretation can be obtained after using deviations from the means of the variables included in (2b).

[4] A central problem related to the use of input measures remains the unknown relation between R&D investment and the output of the innovation process. This concerns – among others – the time delay between R&D investment and innovation success, or the depletion of technological opportunities built up by the history of R&D investment.

measures would aggravate the endogeneity problem[5] as in this case the productivity equations will contain an output measure as one of the explanatory variable. A second point concerns the definition of innovation output. Which choice between the available alternatives should be made? For instance, should one use (the share of) new products or new and improved products, products new to the firm or new to the market? Third, is innovation output measured in this way equivalent to the output of a knowledge-production function or, more precisely, the result of applying the knowledge-capital accumulation equation given by (2b)?

4.3 Adaptations of our previous model

4.3.1 The derivation of an enhanced productivity-growth equation

Recent studies (see e.g. Crépon et al., 1998, and Klomp and Van Leeuwen, 2001) have exploited the new CIS data in a structural modelling approach. These approaches claim that it is not differences in *innovation investment* (or more specifically, the history of R&D investment), but rather differences in *innovation output* that determine the observable differences in productivity (growth). In this section an extension of the model used in Van Leeuwen and Klomp (2001) is presented. The proposed model aims to capture the theoretical issues of the preceding section and also makes a more extensive use of the CIS data than does the study of Crépon et al. (1998). Similar to Klette (1996), a firm's total sales are used as the starting point for the model derivation but, contrary to his study, sales performance of firms is embedded in a market-share model. Therefore, the model proposed here is similar to that of Klette and Griliches (1996), with the difference that an innovation output measure is used to capture the impact of 'demand-shifts' on sales-per-employee growth. This adaptation can be argued as follows. Saying that innovation output is similar to relative product quality, by definition implies that innovating firms are operating on markets characterised by horizontal product differentiation. Thus, one may expect that successful innovators have the discretion of market power; this makes their relative prices endogenous.

Let the differential equation for the market share of firm i operating on market (industry) I be given by

$$\Delta q_i^d - \Delta \overline{q}_I = \Delta d_i + \eta \Delta (p_i - \overline{p}_I)^6. \tag{3a}$$

In (3a) q_i^d, p_i and $\overline{q}_I$ denote respectively the demand and own price (index) of firm i and total sales of market (industry) I. Furthermore, η represents the demand elasticity with respect to

[5] This econometric problem also complicates the use of traditional R&D models as one may expect that the R&D investment decision may be dependent on firm performance.

[6] Equation (3a) is the 'long-difference' form of the market-share, where the 'long-difference' operator Δ refers to annualised growth rates calculated for the periods 1994-1996 and 1996-1998.

relative prices (or stated otherwise: the 'own' price index relative to the aggregate deflator for industry *I*) and Δd_i summarises the contribution of 'demand-shifting' variables to the growth rate of a firm's own demand relative to the growth of exogenously given sales opportunities, represented by $\Delta \overline{q}_I$.

The proposed model adopts a parametrisation of the 'demand-shifter' that uses the data on cross-sectional differences in relative product quality observed in CIS. More precisely, $\Delta d_i = \phi S_i$ is used, with S_i the share of new (or new and improved) sales in total sales. Taking into account the definition of the growth rate of deflated revenues (Δr_i), expressed as:

$$\Delta r_i = \Delta(q_i + p_i) - \Delta \overline{p}_I, \tag{3b}$$

and after equation demand and output, and combining (3a) and (3b) with a traditional gross-output-production-function model,[7] this yields

$$\Delta r_{it} = \varepsilon(\alpha \Delta c_{it} + \lambda \Delta m_{it} + \beta \Delta l_{it}) - \frac{1}{\eta}\Delta \overline{q}_{It} - \frac{\phi}{\eta} S_{it} + e_{1it}, \tag{3c}$$

where ε represents the inverse of the mark-up factor,[8] e_{1i} is a disturbance term and a time subscript is added to distinguish between observation periods.

In the empirical application, the productivity equivalent of (3c) is used after adding a constant term and dummy variables to capture a general trend and the impact of process innovation on a firm's revenue-per-employee growth respectively.[9] Therefore, the empirical specification for the revenue-per-employee equation of the model reads:

$$\begin{aligned} \Delta r_{it} - \Delta l_{it} &= \mu + \varepsilon\alpha(\Delta c_{it} - \Delta l_{it}) + \varepsilon\lambda(\Delta m_{it} - \Delta l_{it}) + \varepsilon(\alpha + \beta + \lambda - 1)\Delta l_{it} \\ &\quad - \frac{1}{\eta}\Delta \overline{q}_{It} - \frac{\phi}{\eta} S_{it} + \xi D_{proc,it} + e_{2it}. \end{aligned} \tag{4}$$

The estimation of (4) yields an implicit estimate of the contribution of innovation to multi-factor-productivity growth (MFP), given by $-(\hat{\phi}/\hat{\eta})\overline{S}$, and also controls for biases in the returns-to-scale estimates.[10] Note that, contrary to the basic framework (see Appendix 4.1),

[7] The model uses as inputs into production ordinary physical capital (C), labour (L) and material inputs (M) (see appendix 4.1).

[8] The inverse of the mark-up factor is related to the price elasticity of demand as follows: $\varepsilon = (\eta + 1)/\eta$

[9] This dummy variable takes on a value of one if firms stated to have implemented process innovation and zero otherwise.

[10] $\overline{S}$ represents the average share of innovative sales and the estimate for $\alpha + \beta + \lambda - 1$ in (4) represents the deviation from constant-returns-to-scale.

innovation investment is no longer interpreted as a separate input. Instead, the model assumes that differences in innovation intensities are transmitted to differences in revenue-per-employee growth to the extent that a firm's investment endeavour has been successful.

4.3.2 Linking the revenue model to the innovation process

The next step is to embed (4) in a structural model that is sufficiently flexible to capture important features of the innovation process and that takes into account the joint endogeneity of innovative sales and sales-per-employee growth. With sufficiently flexible I mean that this model should be able to account for within-firm time interdependencies of knowledge production as well as the various interactions between internal and external knowledge bases. However, this is a daunting task in view of the available data and the intricacies involved. Many variables collected in CIS are of a qualitative nature and how to use these data optimally together with the continuous variables for innovation investment and innovation output remains an open question. A related problem is that a firm's technological environment may affect its innovation investment and its level of innovation output achieved at the same time.

A recurrent conclusion of previous research (see e.g. Cohen and Levinthal, 1989, Leiponen, 2001, Veugelers, 1997, and Veugelers and Cassiman, 1999), is that the technological environment of a firm may affect its organisational arrangements. Firms absorb knowledge from the environment via supplier-producer-customer-interactions, the use of available information sources in addition to building up and maintaining their own knowledge bases via R&D investment and (R&D) co-operation. The choice between the 'make', 'buy' or 'make and buy' option at the one hand, or between 'formal' and 'informal' R&D or – more general – innovation at the other hand, may have diverging impacts on the level and composition of innovation cost. Moreover, utilising the technological environment may also contribute to innovation output more directly. For instance, one can imagine that firms innovate by exploiting the available information sources or by relying on informal innovation co-operation even without spending one dollar on R&D.

In order to account for the complementarity between internal and external knowledge bases and knowledge flows between firms, R&D investment decision and the level of innovative sales achieved are assumed to be jointly dependent on various firm-specific innovation characteristics.[11] In addition, the within-firm time interdependencies is modelled for the two stages of the innovation process by adopting a dynamic specification for the R&D intensities (denoted by *R/Q*) as well as for the (logarithm of the) share of new sales in total sales.[12] This yields the following two equations

[11] A description of all instrumental variables is given in appendix II.

[12] I use the R&D intensity form and the logarithmic transformation of *S* in (5a) and (5b) because this enables a comparison with, for example, Crépon et al. (1998) and Van Leeuwen and Klomp (2001). Furthermore, to be consistent with (5a) and (5b), I replaced *S* in (4) by $\exp\{\ln(S)\}$.

$$(R/Q)_t = \pi_{10} + \pi_{11}(R/Q)_{it-1} + \pi_{12}\ln(S_{it-1}) + X'_{1t}\Pi_{13} + Z'_{1t}\Pi_{14} + e_{rt} \tag{5a}$$

$$\ln(S_{it}) = \pi_{20} + \pi_{21}\ln(S_{it-1}) + \pi_{22}(R/Q)_{it} + X'_{2t}\Pi_{23} + Z'_{2t}\Pi_{24} + e_{sit}\,, \tag{5b}$$

The capital Π's in (5a) and (5b) denote vectors of parameters associated with the instrumental variables (other than the lagged dependent variables included). We collect these variables into two vectors *X* (for production survey data) and *Z* (for innovation survey data). The identification of the model rests on the partitioning of these vectors across the two equations. A similar partitioning to that used in Van Leeuwen and Klomp (2001) has been chosen (see also Appendix 4.2):

$X = \{MS_{t-1}, \Delta\overline{q}_I, l_{t-1}, CF_{t-1}\}$;

$Z = \{D_{pull1}, D_{pull2}, D_{push1}, D_{push2}, SCIENCE, OTHER, D_{co-op}, D_{R\&D}\}$,

$Z_1 = \{Z, D_{subs}\}$, $X_1 = \{MS_{t-1}, \Delta\overline{q}_I, l_{t-1}, CF_{t-1}\}$,

$Z_2 = \{Z, D_{proc}, PAVIT\}$ and $X_2 = \{\Delta\overline{q}_I, l_{t-1}\}$.[13]

Note that (5a) generalises (2b) and that system (5) as a whole can be used to compare the differences between the persistence of R&D input and innovation output. In addition, an estimate for the impact of the initial level of innovativeness (represented by $ln(S_{t-1})$) on the current R&D endeavour is obtained. Furthermore, system (5) can be reduced to a static version by removing the lagged endogenous variables, thus enabling a comparison with our previous research.

4.4 The data

The data used in this paper are obtained by matching the two waves of CIS to the production surveys for manufacturing. In general, the two innovation surveys asked the same questions and were based on the same sampling frame that underlies the production surveys. Thus, in principle, matching the two innovation surveys is straightforward. However, an exception should be made for few enterprises that have their R&D function centralised in special units. As their innovation data for 1996–1998 were collected in a different way than the corresponding data for 1994–1996 (CIS2), these data have not been used.

The model makes extensive use of market (industry) variables. Therefore, industry data on nominal sales were first constructed for the years 1994, 1996 and 1998. Using the raising factors of the underlying production surveys the value of total sales was calculated on the ISIC three-

[13] *PAVIT* denotes a set of dummy variables that represent the industry classification of firms according to technology regimes. See Appendix 4.2 for an explanation of the other instruments collected in *X* and *Z*.

digit level for each year. Subsequently, these data were linked to the corresponding industry price indices for total sales and material usage.[14] In the next step a clean set of complete firm-level production survey data was constructed for the two periods covered by the innovation surveys. In order to obtain two short panels, firms with complete production survey data in 1994 and 1996 or 1996 and 1998 were selected. The cleansing rules eliminated firms with a negative score for their value added or missing data on employment, the cost of material usage and depreciation costs. In addition, and to safeguard against a mismatch with our industry data, firms that showed a change of the (3-digit) ISIC classification were also eliminated.[15]

To estimate the parameters of the productivity growth equation of our model, data on labour input, material usage and physical capital are also needed. The first two variables are readily available, although for labour input 'head counts' (the number of employees) are the only variable available. Unfortunately, not uncommonly for this type of data, measures of capital inputs raise more problems. The capital input measure used to estimate the models is approximated by the depreciation costs (deflated with the price index for total sales) available in the production surveys.[16] Similarly, the other nominal variables in the data set were deflated after linking the industry data to the firm-level data, by applying the industry sales - or material price indices to all firms within the corresponding industry. In the final stage of the data construction, the two innovation surveys were linked to the corresponding production survey panels after removing firms with a suspiciously high innovation intensity.[17]

Table 4.1 Summary of the data sets available for manufacturing

	1994-1996	1996-1998	1994-1998
Complete PS data	4134	5087	3180
Covered in CIS	2516	3012	1160
• Innovative	1428	1618	758
• Non-innovative	1088	1394	402

[14] The price indices represent the average change in prices compared to (base-year) 1990. Their level of detail varies between the two- and three-digit level of the ISIC industry classification of firms, with a greater level of detail for the sales deflators than for the price indices concerning material usage.
[15] A firm for which the 3-digit industry classification was changed in 1994–1996 has been eliminated from the panel for this period. Nevertheless, this firm can be included in the panel for 1996–1998, provided that its classification did not change in the latter period.
[16] This financial measure is related to the capital stock but does not reflect directly the capital service flow. Tax laws, vintage structures and type distribution of the assets, and cyclical capital utilisation all cause differences between the depreciation data and the desired measure of real capital input.
[17] Firms covered in CIS2 or CIS2,5 were removed from the data if their innovation intensity (total innovation cost scaled by nominal sales) exceeded 50%.

A summary of the data available after the before mentioned steps is given in Table 4.1. It should be noted that the second period covers many more very small firms than the first period. This applies to the production survey as well as to the innovation survey. Nevertheless, the CIS coverage ratios for the two periods are more or less equal (about 60%). For the coverage with respect to innovating firms, the result is similar: the share of innovating firms as a percentage of all firms covered by CIS differs only slightly between the periods covered by CIS2 and CIS2,5. However, if a balanced innovation panel is used, then the coverage ratio of CIS decreases to 36% (see the last column of Table 4.1). This unexpected result may have different causes and deserves further investigation. On the other hand, it can be seen that the use of a balanced innovation panel may invoke another selectivity problem, as the percentage share of innovating firms is larger for the balanced innovation panel (65% compared to 57% in 1994–1996 and 54% in 1996–1998). The latter result may be due to the combined effect of a higher probability of survival and a higher persistence of innovativeness for larger firms.

In closing, it should be noted that the definition of ‘innovativeness’ used in this study differs from the one used in Statistics Netherlands (2000). In the present study, firms that responded to CIS are labelled 'innovative' if they have a complete set of data on its innovation investment, innovation output and the qualitative variables referring to the technological environment. By contrast, Statistics Netherlands (2000) uses a broader definition, and firms are classified ‘innovative’ if they have carried out innovative activities in some way. In the latter definition, firms are considered to be ‘innovative’ even if they did not actually implement any product or process innovation in the period considered. For these firms the variables included in the model discussed above are not available.

4.4.1 A comparison of the performance of innovating and non-innovating firms

Tables 4.2a and 4.2b present some simple descriptive measures for the key variables used in this study, enabling a comparison of the performance of innovating (I) and non-innovating (N) firms for 1994–1996 and 1996–1998. On the whole, the tables confirm our previous result (Klomp and Van Leeuwen, 2001) that innovating firms are performing better than non-innovating firms. This conclusion applies to all performance measures included, except for the industry variables. The latter result shows that general business conditions did not favour innovating firms in particular. The most striking difference between the two periods concerns the growth rate of employment. The accelerating growth of industry sales in 1996 – 1998 shows up in a positive employment growth in this period, in particular for innovation firms. However, I do not observe a similar acceleration of sales-per-employee growth. Moreover, the acceleration of labour productivity growth (measured as value-added-per-employee) appears to be modest.

Table 4.2a Descriptive statistics for selected variables in 1994 – 1996[1]

Variable	Median	Q1	Q3	SD
Growth rate of :[2]				
Employment (I)	0.0	-3.8	4.6	11.0
Employment (N)	0.0	-4.6	4.6	13.5
Value added per employee (I)	2.0	-4.5	8.6	15.8
Value added per employee (N)	1.4	-5.6	8.9	19.2
Sales per employee (I)	3.3	-2.6	9.6	13.8
Sales per employee (N)	2.6	-3.9	9.7	16.2
Industry sales (I)	3.6	1.2	6.9	7.7
Industry sales (N)	3.5	1.4	5.8	6.7
Levels:				
Market share 1994 (%) (I)	0.6	0.2	1.9	7.6
Market share 1994 (%) (N)	0.2	0.1	0.6	4.1
Employment 1994 (I)	89	53	175	1152.8
Employment 1994 (N)	42	28	73	224.9
Profitability 1996 (%) (I)	9.8	5.1	16.5	13.9
Profitability 1996 (%) (N)	8.4	3.3	14.9	14.4
Value added per employee 1996 (I)[3]	97.0	76.5	131.7	82.2
Value added per employee 1996 (N)[3]	84.4	66.3	109.6	82.3
Sales per employee 1996 (I)[3]	251.1	184.3	373.8	422.0
Sales per employee 1996 (N)[3]	212.6	151.7	317.5	565.4

[1] Number of innovative firms (I) is 1428; Number non- innovative firms (N) is 1088.
[2] Annualised growth calculated over the period 1994 – 1996.
[3] In NLG thousand.

Table 4.2b Descriptive statistics for selected variables in 1996 – 1998[1]

Variable	Median	Q1	Q3	SD
Growth rate of :[2]				
Employment (I)	1.3	-2.5	7.0	14.0
Employment (N)	0.4	-3.2	7.7	17.6
Value added per employee (I)	2.3	-4.8	9.8	17.8
Value added per employee (N)	1.7	-6.7	10.3	21.9
Sales per employee (I)	3.2	-3.3	9.7	17.4
Sales per employee (N)	2.2	-5.5	10.1	21.6
Industry sales (I)	5.4	2.3	6.9	5.3
Industry sales (N)	5.4	1.4	6.9	5.9
Levels:				
Market share 1996 (%) (I)	0.4	0.1	1.6	6.8
Market share 1996 (%) (N)	0.2	0.1	0.5	4.1
Employment 1996 (I)	74	34	159	1077.5
Employment 1996 (N)	30	15	57	170.7
Profitability 1998 (%) (I)	10.1	4.8	16.4	13.7
Profitability 1998 (%) (N)	9.9	4.3	18.0	16.6
Value added per employee 1998 (I)[3]	99.0	77.7	133.4	138.9
Value added per employee 1998 (N)[3]	88.4	67.4	118.8	72.3
Sales per employee 1998 (I)[3]	264.7	187.5	394.6	834.6
Sales per employee 1998 (N)[3]	218.1	150.5	337.9	1751.3

[1] Number of innovative firms (I) is 1618; Number non-innovative firms (N) is 1394.
[2] Annualised growth calculated over the period 1996 – 1998.
[3] In NLG thousand.

The simple descriptive measures used for the level data also point to some well-known stylised facts as the tables show that size distributions are very skew and that innovating firms are smaller and have higher median values for the market shares. It can also be seen that the different survey design for the period 1996–1998 shows up in a lower median value for employment, both for innovating and non-innovating firms.

4.5 Estimation results

4.5.1 Selectivity issues

In this section, the estimation results for the various implementations of the full model are presented. In all implementations the estimated system contains the productivity-growth Equation (4), but I shall iterate on the functional form of the equations that refer to the innovation process. In any case, the estimation of the system takes into account the simultaneity of innovation investment, innovation output and productivity growth. The data allow a break-down for the total of innovation cost and I can also choose between different measures of innovative sales. In order to keep things tractable, and to preserve the link with previous R&D-productivity research, R&D intensity was chosen as the measure of inputs into innovation. For the output side of the innovation process, I have chosen to compare the model estimates obtained after using two alternative measures: the share of new sales (new to the firm) in total sales; and the share of new and improved sales in total sales. I begin by using the second measure[18] and then recalculate the models using the first definition of innovation output.

In the estimation procedure I try to correct for possible biases due to selectivity problems. *A priori* reasoning suggests that the emergence of such problems may be dependent on the adopted specification for the innovation model. For instance, if (5a) and (5b) are used as the model for the innovation process, then the complete system can only be estimated using the firms that were innovative in the two periods considered. In this case a severe loss of information is encountered. This problem can be overcome by transforming (5a) and (5b) into a static version by removing the lagged dependent variables from the equations.

However, this change of modelling strategy seems not be trivial in view of the very nature of the process of 'knowledge production' and the measure used for the output of this 'production process'. It may be the case that part of the sample attrition is due to discontinuities in knowledge creation (or more precisely the generation of new or improved products) at the firm level. Put simply: 'the fact of having achieved new or improved sales in 1994–1996 may reduce the incentive to innovate in 1996–1998, as the technological opportunities may be depleted'. All this is tantamount to saying that a problem of endogenous attrition may be encountered if a dynamic innovation model is used. Note that the selectivity issue can be carried over to the use

[18] This measure has also been used in previous research (Van Leeuwen and Klomp, 2001).

of a static version of (5a) and (5b): a situation might arise in which firms facing favourable sales opportunities have less incentives to be engaged in innovation.

Table 4.3 Results of the innovation input - and innovation-output equation

Type of model	Dynamic model[1]		Pooled model[1]	
	Est.	T	Est.	T
Number of firms	758		3046	
A) R&D intensity 1996 or 1998				
Constant	2.792	2.0	6.269	7.2
R&D intensity 1996	0.434	24.2		
Innovation output 1996	-0.014	-0.2		
Size 1994 or 1996	-0.255	-2.0	-0.784	-7.4
Market share 1994 or 1996	0.042	5.8	0.034	8.2
Subsidy awarded	0.269	1.1	0.582	3.9
Cash-flow ratio 1994 or 1996	-0.004	-0.6	-0.005	-1.7
Permanent R&D facilities	0.505	1.6	0.895	4.7
Innovation co-operation	0.156	0.8	0.258	2.1
Technological opportunity 'Science'	0.247	2.9	0.544	13.5
Technological opportunity 'Other'	0.062	0.5	0.150	2.3
Demand-pull important	-0.108	-0.2	-0.155	-1.0
Demand-pull very important	0.029	0.1	0.023	0.1
Technology-push important	0.182	1.0	-0.181	-1.6
Technology-push very important	-0.016	-0.1	-0.220	-2.0
Industry sales growth 1994 - 1996 or 1996 – 1998	0.001	0.7	0.042	6.2
Period dummy			-0.294	-2.4
Heckman's selectivity correction	-2.912	-1.9	-2.250	-6.3
Pseudo R^2	0.522		0.169	
B) Innovation output 1996 or 1998[2]				
Constant	-5.624	-1.5	-4.790	-16.6
Innovation output 1996	0.295	2.9		
R&D intensity 1996 or 1998	0.067	0.5	0.615	3.9
Size 1994 or 1996	0.135	0.5	-0.036	-0.9
Permanent R&D facilities	0.490	3.0	0.237	1.1
Innovation co-operation	0.174	1.1	0.002	0.0
Technological opportunity 'Science'	0.056	0.6	-0.025	-0.5
Technological opportunity 'Other'	0.230	3.2	0.237	4.0
Demand-pull important	2.025	9.9	0.839	6.7
Demand-pull very important	2.159	9.8	0.838	6.6
Technology-push important	0.033	0.2	-0.063	-0.6
Technology-push very important	-0.267	-1.9	-0.114	-1.1
Industry sales growth 1994 - 1996 or 1996 – 1998	0.003	0.2	-0.026	-2.7
Process innovation implemented	0.252	1.6	0.601	7.6
Period dummy			0.512	4.4
Heckman's selectivity correction[3]	1.096	0.3	x	
Pseudo R^2	0.354		0.088	

[1] The 'dynamic model' covers the 1996 - 1998, the 'pooled' model the periods 1994-1996 and 1996-1998.
[2] Calculated as the (logarithm of the) share of new and improved products in total sales.
[3] I did not include a selectivity correction for the pooled model as the preliminary Tobit selectivity analysis did not indicate a selectivity problem.

The usual way to account for this type of problems is to apply Generalised Tobit models to the equations of the dynamic or static innovation model. These models have been applied as a first step in the estimation procedure. By doing so, the joint dependence on the available exogenous variables can be assessed for the probability of being innovative as well as for the dependent variables of the innovation equations. To save space, the results will not be discussed in great detail in the present paper (see Appendix 4.3 for the model estimates). The main conclusion is that the selectivity problem is more severe for innovation inputs than for innovation output.

The next step consists of finding a way to control for possible selectivity biases of the estimates of the full model. This has been achieved as follows. Dependent on the results of the Tobit analysis, selectivity-correction terms derived from Heckman's two-step method were added. Furthermore, and only for the full model that uses the static innovation equations, time dummy variables were added to all equations of the full model to control for period-specific effects. It should be born in mind that the dynamic version of the full model is estimated for the period 1996–1998, and uses the data for the 758 firms that were innovative in 1994–1996 as well as in 1996–1998 (Table 4.1).[19] The full model, with the static version of the innovation equation included, uses the 3046 firms that were innovative in either 1994–1996 or in 1996–1998.

The two versions of the full model are estimated with the help of the method of Full Information Maximum Likelihood (FIML). The FIML estimates are presented in Tables 4.3 and 4.4. First I look at the estimates for the equations of the innovation process, thereby focusing on two central themes: 1) the persistence of innovativeness and 2) the returns to R&D investment.

4.5.2 The estimates for the innovation equations

The first, and most notable, point to observe is that the estimates for the lagged dependent variable in the R&D-intensity equation, as well as the lagged dependent variable in the innovation-output equation are statistically significant and that the estimate is higher (and estimated with more precision) for R&D-intensities than for innovation-output. This result suggests that there is less persistence when innovation is measured from the output side than when it is measured from the input side of the innovation process. Apparently, the often quoted stylised fact that differences in R&D intensities across industries are persistent cannot be carried over to the output of knowledge production. Moreover, the coefficient of the lagged R&D intensity presented in Table 4.3 may be considered too low to make a very strong statement about its persistence on the basis of our data.[20] In any event, the obtained estimates indicate that,

[19] The data for 1994-1996 were used to construct the lagged dependent variable in the innovation equations.
[20] Note that this stylized fact has been often found after using other types of data, e.g. time series data for industry aggregates or long R&D time series data of very large enterprises.

at least for innovative sales, there is a strong tendency towards convergence when using firm-level data.[21] As mentioned above, the results for innovative sales may be due to a depletion of technological opportunities. One can imagine that this source of non-persistence is far more valid at the firm level than in the aggregate, where the decrease of innovative sales of a particular firm is counterbalanced by an increase of innovative sales of other firms. This leads to the conclusion that there is much turbulence at the firm levels, and much turbulence at the product level, hidden behind the observed regularity of aggregate statistics.[22]

From this point of view it is also understandable that the returns to innovation investment to innovation output (represented by the coefficient of the contemporaneous R&D intensity in the innovation-output equation of the model) are small and statistically insignificant in the dynamic model. If the level of product quality achieved captures the history of a firm's R&D endeavour (and the technological opportunities of this firm are depleted), then the innovation opportunities of the most recent R&D investments may be small. This is the basic conjecture of the models of Hall and Hayashi (1989) and Klette (1996).[23] In the dynamic model, the initial level of 'innovativeness' in terms of innovation output is controlled for. Thus, the estimate of the contemporaneous R&D intensity in the innovation-output equation of the dynamic model seems to corroborate Hall and Hayashi (1989) and Klette (1996).

However, this point deserves further reflection for two reasons. Firstly, how should this result be understood, given that I also obtained a much higher estimate for the returns of innovation investments to innovative sales in the static model, where it is about 0.6 and, moreover, rather significant? Secondly, how to explain the pattern of the estimates for the variable that controls for the presence of permanent R&D in the two equations? The dynamic model contains two different 'forms of control' that are related to the same phenomenon. First, let us compare the corresponding estimates for the two versions of the innovation-input equation. The significance of the estimate for the variable that controls for the presence of permanent R&D facilities is much smaller in the dynamic version of the model than in the 'static' equivalent. This should not be surprising, as the dynamic model is aimed at an estimation of R&D persistence and this persistence has also been captured in the estimate of the lagged R&D intensity.

The next step is to look at the innovation-output equation. The most striking difference between the two versions of the model is the low and insignificant estimate for the R&D intensity in the dynamic model and a much higher (and rather significant) estimate in the static

[21] It should be remembered that the models use the broadest definition of innovative sales available, i.e. the share of new and improved products in total sales.

[22] To give an example: the simple arithmetic average share of new and improved sales in total sales for 1994 – 1996 (calculated using the 1428 firms of table 4.2a) was about 26%. This is almost equal to the corresponding average for 1996–1998 (calculated using the 1618 firms of table 2b). The same regularity can be observed after weighting the data (see e.g. Statistics Netherlands 1998, and, Statistics Netherlands, 2000).

[23] See the summary of their models given in Section 4.2.1.

model. By contrast, it can be seen that the impact of performing R&D on a permanent basis is small and insignificant in case of the static version but larger and rather significant in the dynamic model. Thus, these estimates seem to represent contradictory results. However, there are reasons to question this interpretation. One can imagine that the level of R&D-knowledge stocks achieved is dependent on the nature of R&D investment. A firm that performs R&D on a permanent basis may have fewer difficulties in building up knowledge stocks than firms that perform R&D incidentally. Furthermore, one can imagine that the initial level of innovative sales has captured the history of R&D investment to the extent that knowledge-stocks were productive in terms of innovative sales. In the static model I do not control for the past. Therefore, it is not very surprising that 'performing R&D on a permanent basis' is a better predictor for differences in R&D intensities than for differences in innovative sales. However, in the dynamic model, I do control for the past at both sides of the innovation process. Nevertheless, I obtained a significant contribution to innovative sales of performing R&D permanently.

Another, and perhaps more interesting, explanation for the estimated differences in returns to the current R&D endeavour may be related to the fact that the static model uses many more firms. As a result of the non-rivalry of innovation and (non-intended) 'spill-over' effects to competitors, there are 'new innovators' or 'innovation imitating' firms that were not observed earlier. Such a mixture of 'old' and 'new' innovators – by definition – can be taken better into account in the static model. Furthermore, the emergence of 'new' innovators may explain – in line with the conjecture of Klette (1996) – why the returns to current R&D endeavour are higher in the static innovation model than in the dynamic version of this model.

All in all, these results make a very strong plea for the importance of performing R&D on a permanent basis. They also clarify why we cannot simply rely on R&D intensities alone. However, at the time, the results stress that the use of firm-level innovation panel data may not capture all the salient features of the innovation process. Anyway, the results presented in Table 4.3 underline the benefits of using variables that refer to the organisational aspects of innovation processes and a firm's interaction with its technological environment. As to the latter, it can be seen that our previous results are confirmed for other explanatory variables: I obtained a similar pattern for the impact of the technological opportunity variables "*SCIENCE*" and "*OTHER*" in the two equations as in Klomp and Van Leeuwen (2001). Again, and in line with the 'absorptive-capacity' hypothesis of Cohen and Levinthal (1989), "*SCIENCE*" appears to be more important for predicting differences in R&D intensities and "*OTHER*" for predicting differences in innovative sales.[24] Furthermore, the correspondence with the conclusions of our previous research also applies to other results:

[24] The decrease in significance for the estimated impact of *SCIENCE* to innovation investment when using a dynamic model can be explained by the fact that the contribution of this variable has already been captured in the estimate for the lagged dependent variable.

- Conditional on selection, there appears to be a negative relation between firm size and R&D intensities (see also Cohen and Klepper, 1996);
- Large firms do not show a better innovation performance in terms of innovation output than small firms;
- The implementation of process innovation contributes positively to innovation output (see also Bartelsman et al., 1998);
- Innovation seems to be predominantly a 'demand-driven' process (see the estimates for the variables that refer to the objectives underlying innovation).

4.5.3 The contribution of innovation to productivity growth

This subsection discusses the estimation results of the revenue-per-employee model presented in Table 4.4. In particular, it pays attention to the contribution of innovation to multi-factor-productivity (MFP) growth. According to the theoretical exposition of Section 4.3, this contribution is given by $\hat{\gamma}\overline{S} = -(\hat{\phi}/\hat{\eta})\overline{S}$. Therefore, by focusing on innovative sales, the measure for the contribution of innovation to productivity growth follows the quality ladder or product variety model of Grossman and Helpman (1991). Indeed, looking at our firm-level data, it can be observed that many innovations are incremental. It can be verified, that a substantial part of the innovating firms have only implemented product improvements. Furthermore, the discussion of the estimates of the two versions of the innovation model presented in Table 4.3 points to the presence of different forces. A rather low persistence of innovativeness (in terms of having achieved new and improved sales) can be seen when tracking the innovation performance of individual firms over time. On the other hand, a higher return to the current R&D endeavour has been estimated if 'new' innovators' or 'innovation imitating' firms are taken into account.

Unfortunately, and by construction, data on the innovation-investment history of these 'new' innovators are not available.[25] I have tried to circumvent this problem by using two alternative measures for innovation output. The full model was recalculated after redefining innovation output as the share of *new sales* in total sales and then compared the results for the MFP-contribution to productivity growth of the two measures of innovation output. Furthermore, the two definitions of innovativeness were applied to the innovation panel as well as to the complete sample (including the firms that were only existent in one wave of CIS). It goes without saying that the different models applied yield different estimates for the innovation-

[25] This is a consequence of the fact that only the current innovation costs are collected if firms stated to have implemented product or process innovation.

output variable of the productivity-growth model and that the differences between the averages for the innovative output measure chosen should also be taken into account.[26]

By doing so, an estimate for the contribution of innovation to MFP growth is obtained that lies in between 0.4% and 0.9%. It can be seen from Table 4.4, that these estimates are highest for innovation output defined as the share of new sales in total sales. It is also interesting to see

Table 4.4 The results for the revenue-per-employee equation[1]

Use of innovative sales	New sales		New and improved sales	
	Est.	T	Est.	T
A) Dynamic model				
Number of firms	510		758	
Constant	0.518	0.5	-0.046	-0.0
Physical capital	0.017	1.2	0.006	0.5
Labour	0.076	1.7	0.132	3.3
Material inputs	0.781	10.7	0.761	11.4
Dummy process innovation applied	-1.155	-1.7	-0.754	-1.0
Share of innovative sales	0.055	1.7	0.015	1.0
Returns to scale	-0.126	-1.5	-0.101	-1.2
Inverse of mark-up	0.896	10.9	0.913	12.3
Share of innovative sales in total sales	10.1		27.5	
Contribution of innovation to MFP (%)	0.6		0.4	
R^2	0.630		0.550	
B) Pooled model				
Number of firms	1929		3046	
Constant	-1.001	-2.1	-0.317	-0.9
Physical capital	0.020	4.1	0.014	3.5
Labour	0.117	10.5	0.142	15.0
Material inputs	0.747	28.1	0.749	36.2
Dummy process innovation applied	-0.196	-0.4	-0.245	-0.7
Share of innovative sales in total sales	0.115	6.8	0.030	3.8
Returns to scale	-0.116	-3.8	-0.095	-3.9
Inverse of mark-up	0.966	29.0	0.946	38.2
Share of innovative sales	8.2		26.4	
Contribution of innovation to MFP (%)	0.9		0.8	
R^2	0.714		0.683	

[1]All models use annualised growth rates.

that the latter model version yields the best ‘fit’ to the data. For the models that use new sales, one can observe a higher precision of the corresponding estimates as well as a higher coefficient

[26] If we change the definition of innovation output to cover new sales only, then we can use 510 firms in the dynamic model and 1929 firms in the model that uses all available data.

of determination (R^2) than in the variant that uses a less discriminating definition of innovation output, irrespective of specification for the innovation model used. On the basis of these criteria – and because it covers many more firms – the model that uses all available data is adopted as the preferred model.

In closing, let us take a look at the other estimates of the revenue model. It can be observed that the precision of the production elasticities of the model increases with the sample size used and that we have a tendency to decreasing returns to scale. However, this conclusion should be interpreted with care as, in general, a rather low (and in some cases insignificant) estimate for the production elasticity of ordinary physical capital. The latter result is probably due to the approximate measure used for this variable, taking also into account that firm-level data of a times series type rather than cross-sectional differences in levels were used.[27] Furthermore, it should be noted that the estimates control for the importance of process innovation. In general, the contribution of process innovation to sales-per-employee growth appears to be insignificant. Comparing this result with the estimates of the corresponding variable found in the innovation-output equation, one has to conclude that process innovation contributes relatively more to innovative sales than to non-innovative product lines. A final notable result concerns the estimate for the mark-up factor included in the models. Here, the most sensible results are observed for the model that uses new sales as the measure of innovativeness and that was applied to the panel of innovative firms. This result seems in line with the *a priori* expectation that the underlying market-share model yields the most sensible representation for those firms that are continuously engaged in innovation.

4.6 Summary and conclusions

In this paper I have presented the first results of an attempt to assess the importance of innovation for inter-firm differences in productivity growth using two similar CIS surveys and - after linking these surveys - to the Production surveys for the same firms, using the innovation panel to investigate a number of theoretical issues. I have combined recent lines of research in a structural modelling approach that allows the contribution of innovation to multi-factor-productivity (MFP) growth to be interpreted as a ‘demand-shifting effect’. The model rests on the basic assumption that innovation is predominantly ‘demand-driven’, and that its contribution to productivity growth thus should be measured along the quality ladder or product variety model of Grossman and Helpman (1991). The model also accounts for the joint endogeneity of R&D investment, innovation output and sales-per-employee growth. Moreover, I have tried to control for the interaction between internal and external knowledge bases, the within-firm time interdependencies of R&D and innovation output, and the biases in estimation that result from endogenous panel attrition or endogenous selection. Two important points concern 1) a

[27] See, for example Mairesse (1990) for a detailed account of this phenomenon.

comparison of the persistence of R&D investment and innovation output, and 2) a comparison of the contribution to MFP growth based on the innovation panel and based on the set of all firms.

The dynamic model used offers an intuitive form of 'controlling' for the past innovation history, and enables a comparison of the importance of other firm-specific innovation characteristics. The results of this model show that innovation persistence is smaller when measured from the output side of the innovation process than when judged from R&D intensities. This outcome seems to confirm the conjecture of earlier research, that the returns of current R&D endeavours become much lower after controlling for the level of innovativeness already achieved. This result also points to a (private) rate of depreciation of 'knowledge', which is much higher than that applied when constructing R&D-capital-stocks in the traditional way. Furthermore, and in line with the previous result, I obtained a rather small return to the current R&D endeavour for the firms included in the innovation panel. Nevertheless, the estimates of the dynamic innovation model underline the importance of being permanently active in R&D. Controlling for past innovation inputs as well as innovation output, I obtained a significant contribution of performing R&D on a permanent basis to innovation output.

On the other hand, the returns of the current R&D endeavour are very different if the dynamic specification is relaxed, and a restricted and static model is applied to all available CIS data. For this restricted model, a more pronounced and rather significant estimate for the returns of the most recent R&D investment endeavour has been found. Conditional on the assumption that many of the additional firms used in the static model are 'new innovators' with relatively short innovation histories, this result seems to corroborate the conjecture that the returns to R&D are highest for the firms that have low initial knowledge-capital-stocks.

Finally, to explore the sensitivity of the estimate for the implied contribution of innovation to MFP, I performed iterations on the specification for the innovation model and the measures of innovation output available. The results of this sensitivity analysis show that, in most cases, there is a significant estimate for the contribution of innovation to MFP, which varies between 0.4% and 0.9%.

References

Bartelsman, E.J., G. van Leeuwen and H.R. Nieuwenhuijsen, 1998, Adoption of Advanced Manufacturing Technology and Firm Performance in the Netherlands, *The Economics of Innovation and New Technology*, vol. 6, pp. 291 – 312.

Cohen, W.M. and D.A. Levinthal, 1989, Innovation and Learning: The Two Faces of R&D, *The Economic Journal*, vol. 99, pp. 569 – 596.

Cohen, W.M. and S. Klepper, 1996, A Reprise of Size and R&D, *The Economic Journal*, vol. 106, pp. 925 – 951.

Crépon, B., E. Duguet and J. Mairesse, 1998, Research, Innovation, and Productivity: An Econometric Analysis at the Firm Level, *The Economics of Innovation and New Technology*, vol. 7, pp. 115 – 158.

Griliches, Z., 1998, *R&D and Productivity, The Econometric Evidence*, University of Chicago Press, Chicago.

Griliches, Z. and J. Mairesse, 1997, Production Functions : The Search for Identification*, Document de travail CREST 9730*.

Grossman, G., M. and E. Helpman, 1991, Quality Ladders in the Theory of Growth, *Review of Economic Studies*, vol. 58, pp. 43 – 61.

Hall, B., H. and F. Hayashi, 1989, Research and Development as an investment*. NBER Working Paper no. 2973*, National Bureau of Economic Research, Cambridge, Mass., USA.

Klette, T., J. and Z. Griliches, 1996, The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous, *Journal of Applied Econometrics*, vol. 11, pp. 343 – 361.

Klette, T., J., 1996, R&D, Scope Economies, and Plant Performance, *RAND Journal of Economics*, vol. 27, no. 3, pp. 502 – 522.

Klomp, L. and G. van Leeuwen, 2001a, Linking innovation and firm performance: a new approach, *International Journal of the Economics of Business*, vol. 8, pp. 343 – 364.

Van Leeuwen, G., and L. Klomp, 2001b, On the Contribution of Innovation to Multi-Factor-Productivity Growth, *Proceedings of the ECIS Conference on The future of Innovation Studies*, Eindhoven.

Leiponen, A., 2001, Organization of Collaboration: An Empirical Analysis of Knowledge Intensive Business Service Relationships, Working paper Presented at: *The Workshop on Innovation, Technological Change and Growth in Knowledge-based and Service-intensive Economies*, Stockholm.

Lööf, H. and H. Heshmati, 2001, Knowledge Capital and Performance Heterogeneity: A Firm Level Innovation Study, *International Journal of Production Economics*, forthcoming.

Mairesse, J., 1990, Time-Series and Cross-sectional Estimates on Panel Data: Why Are They Different and Why Should They Be Equal?, in. J. Hartog, G. Ridder and J. Theeuwes (eds.) *Panel Data and Labour Market Studies*, North-Holland, Amsterdam, pp. 81 – 95.

Mairesse, J. and M. Sassenou, 1991, R&D and Productivity: A Survey of Econometric Studies at the Firm Level, *Science – Technology – Industry Review*, OECD, 8. pp. 9 – 43.

Statistics Netherlands, 1998, *The Knowledge Based Economy 1998* (in Dutch: *Kennis en economie 1998*, Voorburg/Heerlen, The Netherlands.

Statistics Netherlands, 2000, *The Knowledge Based Economy 2000* (in Dutch: *Kennis en economie 2000*, Voorburg/Heerlen, The Netherlands.

Veugelers, R., 1997, Internal R&D expenditures and external technology sourcing, *Research Policy*, vol. 26, pp. 303 – 315.

Veugelers, R. and B. Cassiman, 1999, Make and buy in innovation strategies: evidence from Belgian Manufacturing firms, *Research Policy*, vol. 28, pp. 63 – 80.

Appendix 4.1 The basic framework for R&D-productivity models

This appendix summarises two well-known specifications for the production model that have been used extensively in the R&D-productivity literature (see e.g. Mairesse and Sassenou, 1991, and Griliches, 1999 chapter 4, for an overview). The model with output (Q) and the inputs physical capital (C), labour inputs (L), material inputs (M) and knowledge capital (K) is approximated by a Cobb-Douglas function. Denoting the logarithms of variables with lower case letters, adding firm subscripts i and omitting time subscripts for the time being, the following difference equations are obtained, where the contribution of R&D to output growth is represented either by the growth of R&D-capital (or equivalently knowledge-capital) stocks (1a) or by the R&D intensities (1b):

$$\Delta q_i = \mu_1 + \alpha_1 \Delta c_i + \lambda_1 \Delta m_i + \beta_1 \Delta l_i + \gamma \Delta k_i + \varepsilon_{1i} \tag{Ia}$$

$$\Delta q_i = \mu_2 + \alpha_2 \Delta c_i + \lambda_2 \Delta m_i + \beta_2 \Delta l_i + \rho (R/Q)_i + \varepsilon_{2i} \tag{Ib}$$

The knowledge-capital stocks (K) underlying (Ia) are constructed using the Perpetual-Inventory Method (PIM), usually applied to ordinary capital investment:

$$K_t = (1-\delta)K_{t-1} + R_t\,, \tag{II}$$

and assuming no depreciation of knowledge-capital stocks ($\delta = 0$).[28]

It is well-known that (Ia) yields an estimate (γ) of the elasticity of output with respect to innovation capital stocks, whereas (Ib) yields an estimate (ρ) of the (gross) private returns to innovation investment or, more specifically, R&D. The relation between these two estimates can be expressed as:

$$\rho \equiv \frac{\partial Q}{\partial K} = \gamma \frac{Q}{K}. \tag{III}$$

Both specifications have the advantage of providing a control for firm-specific and time-invariant differences in production levels, but (Ia) can only be estimated if we have firm-level time-series data for K. However, the construction of R&D-capital stocks at the firm level can

[28] The precise relation between (Ia) and (Ib) is given by $\gamma \Delta k_i = \frac{\rho \Delta K}{Q} = \frac{\rho (R - \delta K_{-1})}{Q} \approx \rho \frac{R}{Q}$.

only be accomplished at the cost of a severe loss of information.[29] In the CIS surveys, a much larger sample of firms is available. Moreover, the data are of a cross-sectional type and this implies that the proposed model should be able to account for the well-known and persistent differences in R&D intensities across industries. For this reason we prefer to use specification (Ib).

Appendix 4.2 The exogenous variables for the innovation equations

For the identification of the model it is necessary to assign exogenous variables to the jointly endogenous variables. The selection of the exogenous variables has been guided by the following considerations. A distinction is made between 1) variables that reflect the objectives underlying innovation, the organisational aspects of a firm's innovation process and its technological environment, 2) financial variables and 3) predetermined firm-specific variables and industry-specific variables that can be considered as exogenously given to the firm.

The first group of variables refer to the objectives underlying innovation. If the replacement of old products or the improvement of the quality of existing products or the extension of market shares and product ranges were rated as important, the dummy variable D_{pull1} takes on a value of one (and zero otherwise), whereas the rating 'very important' is captured by D_{pull2}. Similarly, I constructed two 'cost-push' dummy variables for the objectives 'economising on production costs' (labour cost, cost of material inputs and energy) were considered 'important' (D_{push1}), or 'very important' (D_{push2}). The variables representing the organisational aspects of the innovation process are $D_{R\&D}$ (indicating the presence of permanent R&D facilities), $D_{co\text{-}op}$ (referring to innovating in partnership), and two continuous variables '*SCIENCE*' and '*OTHER*' which were derived from a principal components analysis in order to represent the use of technological opportunities.

The relation between the presence of permanent R&D facilities, 'innovation in partnership' and the two technological opportunity variables ('*SCIENCE*' and '*OTHER*') can be outlined as follows. One may expect a 'cost-push' effect on innovation expenditure of the technological opportunity factor '*SCIENCE*' due to the absorptive capacity argument (see e.g. Cohen and Levinthal, 1989). A co-operation between R&D firms and research institutes or universities requires relatively high internal research skills in order to assimilate the fruits of the co-operation and to internalise and commercialise the knowledge created during the co-operation. Contrary, R&D co-operation with e.g. suppliers, customers and competitors is expected to have lower research competence requirements, a smaller impact on the organisation of firms, and thus a lower 'cost-push' effect on innovation expenditure than the technological opportunity

[29] Similar to other countries R&D surveys in the Netherlands have a long tradition. Nevertheless, the linking across time of R&D data at the firm-level is severely hampered by changes in the survey design or by the difficulty in tracking firms over time as a consequence of mutations in the sampling frame, e.g. due to the merging or the splitting-up of firms.

factor '*SCIENCE*'. On the other hand, as mentioned before, informal innovation co-operation may affect innovation output more directly.

The second category of instruments for the modelling of the innovation process consists of financial indicators. For many firms the innovation expenditures consist to a large extent of investment components, e.g. expenditures on in-house R&D, and/or licenses and patents and equipment purchased for the implementation of process innovation. I assume that these investment type expenditures are affected by the availability of financial resources and for this reason I include in the model two financial variables: the ratio of cash-flow to total sales at the start of the observation period (CF_{t-1}) and a dummy variable that refers to the awarding of innovation subsidies (D_{subs}).

The final category mentioned above consists of the variables derived from the Production surveys and that are assumed to be predetermined or exogenous to the firm. The variables used to serve as an instrument for the endogenous inputs into innovation and innovation output are (the logarithm of) initial employment (l_{t-1}), the initial market shares of firms (MS_{t-1}) and the growth rate of industry sales annual sales ($\Delta\overline{q}_{It}$), already introduced in the main text of the paper. The first variable enables us to test whether the stylized facts of Cohen and Klepper (1996) concerning the relation between R&D and size also apply to our data. The two other instrumental variables are used to capture differences in initial states of competitiveness and exogenously given potentials for sales growth.

Appendix 4.3 Results for the Generalised Tobit models

Variable	R&D intensity 1998			Innovation output 1998		
	Est.	SE	T	Est.	SE	T
Number of firms	758			758		
A) Probit part						
Constant	-0.237	0.213	-1.1	-0.002	0.192	0.0
Size 1996	0.094	0.044	2.1	0.054	0.039	1.4
Market share 1996	-0.006	0.006	-1.0	0.002	0.004	0.5
Own sales growth 1994 - 1996	0.005	0.003	1.9	0.003	0.002	1.4
R&D intensity 1996	0.096	0.010	10.0	0.002	0.015	0.1
Innovation output 1996	0.024	0.019	1.3	-0.031	0.015	-2.0
Industry sales growth 1996 - 1998	0.002	0.007	0.3	-0.003	0.007	-0.5
Cash-flow ratio 1996	-0.001	0.002	-0.4	-0.001	0.002	-0.6
B) Tobit part						
Constant	1.550	0.594	2.6	-1.357	0.438	-3.1
R&D intensity 1996	0.487	0.011	44.1	0.030	0.044	0.7
Innovation output 1996	0.011	0.058	0.2	0.180	0.034	5.3
Size 1996	-0.169	0.105	-1.6	-0.069	0.082	-0.8
Market share 1996	0.037	0.008	4.4			
Own sales growth 1994 - 1996	0.007	0.006	1.2	-0.003	0.005	-0.7
Industry sales growth 1996 - 1998	0.012	0.016	0.8	-0.002	0.015	-0.1
Subsidies awarded	0.268	0.244	1.1			
Cash-flow ratio 1996	-0.002	0.586	-0.3			
Permanent R&D facilities	0.485	0.266	1.8	0.226	0.120	1.9
Innovation co-operation	0.213	0.193	1.1	0.086	0.116	0.7
Technological opportunity 'Science'	0.199	0.089	2.2	0.035	0.060	0.6
Technological opportunity 'Other'	0.042	0.120	0.3	0.116	0.066	1.8
Demand-pull important	-0.121	0.455	-0.3	0.891	0.144	6.2
Demand-pull very important	0.009	0.465	0.0	0.993	0.155	6.4
Technology-push important	0.210	0.172	1.2	0.031	0.125	0.2
Technology-push very important	-0.019	0.199	-0.1	-0.064	0.112	-0.6
Process innovation implemented				0.086	0.123	0.7
σ^2	2.205	0.090	24.5	2.382	0.073	32.6
ρ_{Tobit}	-0.763	0.051	-15.0	-0.986	0.073	-13.4

Chapter 5

Do ICT spillovers matter? Evidence from Dutch firm-level data*

Abstract

This paper presents an empirical analysis of the contribution of Information Communication Technology (ICT) to labour productivity growth in the 1990s, using an extensive panel of firm-level data for Dutch market services. We estimate enhanced production function models that include ICT spillovers as well as innovation as a component of TFP (growth). Additionally, we compare the results of this approach with the growth-accounting approach carried out at the firm level. By doing so, we attempt to reconcile the different pieces of empirical evidence regarding the contribution of ICT to productivity growth reported in the literature so far. It is shown that, after accounting for ICT spillovers, the relatively high estimated elasticities of own ICT capital at the firm level are substantially reduced. So, they are more consistent with findings for aggregated levels reported in growth-accounting studies. Nevertheless, the latter studies do not disentangle the causes of TFP-growth into ultimate causes like productivity growth arising from ICT spillovers. Our results underline that the contribution of those spillovers in the years of the ICT boom was probably more substantial than the contribution of ICT capital deepening.

5.1 Introduction

This paper presents an empirical analysis of the contribution of Information Communication and Technology (ICT) to labour productivity growth in the 1990s, using an extensive panel of firm-level data for Dutch market services.

One of the most impressive ‘stylised facts’ of the previous decade was the economy wide acceleration of ICT investment. This ICT ‘boom’ has given rise to many discussions about the potentials of ICT to produce externalities and, more precisely, the role of ICT in the resurgence of (labour) productivity growth in the second half of the 1990s in some OECD countries, most notably in the US.

The debate has been mainly fuelled, among others, by the unclear relation between ICT use and Total Factor Productivity (TFP) growth.[1] While ICT can affect labour productivity growth via different channels, growth-accounting studies mainly focus on the contribution of ICT capital deepening at the industry level. These studies have documented that ICT investment has contributed to labour productivity growth in the US and EU including the Netherlands (see, e.g. Jorgenson and Stiroh, 2000, Gordon, 2000, Van Ark et al., 2003 and Van der Wiel, 2001a).

---

* This chapter, co-authored by Henry van der Wiel, was published as CPB Discussion Paper No. 26, CPB Netherlands Bureau for Economic Policy Analysis, The Hague, the Netherlands. This research was carried out as a part of the ICT and Productivity (ICA) project of CPB Netherlands Bureau for Economic Policy Analysis. The project was financed and supervised by the Dutch Ministry of Economic Affairs. I would like to thank Piet Donselaar, George Gelauff, Pieter van Winden and Stephan Raes of the Ministry of Economic Affairs, Bert Balk of Statistics Netherlands and Fré Huizinga, Richard Nahuis, Theo van de Klundert and Henk Kox of CPB Netherlands Bureau for Economic Policy Analysis for valuable comments on an earlier draft of this paper. The data analysis reported in this paper was carried out at the Center for Research of Economic Microdata (CEREM) of Statistics Netherlands.

[1] TFP growth represents the residual output growth once the direct contribution of changes in the inputs (e.g. labour, capital) are accounted for.

After controlling for cyclical effects, Gordon (2000) concludes that returns on computer investment in the US are close to zero outside of durable manufacturing. This leads him to rephrase the famous Solow paradox as follows: ‘how could there be such a low payoff to computer investment in most of the (US) economy where computers are located?’ Several researchers have put this question to the testing by applying econometric methods to the industry-level data underlying their growth-accounting results. Surprisingly or not, these econometric studies fail to exhibit a positive impact of ICT on TFP growth (see, e.g. Stiroh, 2002, and Van der Wiel, 2001a).[2]

Nonetheless, it is often suggested that much of the acceleration of TFP growth in the second half of the previous decade came from the ICT boom. The econometric evidence based on firm-level data seems to underline the importance of ICT for boosting (labour) productivity growth. In many cases the econometric ICT capital deepening elasticities are much higher than seems to be ‘consistent’ with the (still) relatively low ICT cost shares. Moreover, evidence seems to support the assumption that the relationship between ICT and TFP is positive. Examples for the US (manufacturing and service) firms are well documented in Brynjolfsson and Hitt (1995, 2000). Similar findings are reported recently for other countries (see, e.g. Hempell, 2002, for Germany and Broersma et al., 2002 and Van Leeuwen and Van der Wiel, 2003 for the Netherlands).

Several explanations can be put forward why the output elasticity for ICT exceeds its (measured) input share at the firm level. The estimated output elasticity of ICT is well measured but not the related inputs due neglecting the role of unmeasured complementary investments including adjustment costs. Second, hidden assets play a considerable role in the relationship between ICT and productivity like (complementary) innovations, organisational practices and firm-specific human capital. Finally, also ICT spillovers could induce a wedge between the output elasticity of ICT and its input share.

Based on this brief overview of studies, we conclude that the effect of ICT on TFP growth is ambiguous. It depends on the level of aggregation (i.e. meso versus micro level) and the method (i.e. econometrics versus growth accounting) used as well. Therefore, which part of the recovery of labour productivity growth is channelled through TFP growth and which part is due to ‘capital deepening’ remains an ongoing debate.

This paper elaborates further on this issue for the Netherlands by placing the contribution of ICT to TFP on the firm level at the centre of interest. It uses both an econometric production function approach and a growth-accounting approach at the firm level. Both approaches are

[2] Similar inconclusive results for the relation between ICT and productivity were reported for the US by Berndt and Morrison (1995). The failures of econometric methods applied to aggregated data may explain why so many studies resorted to growth-accounting methods for analyzing the impact of ICT on productivity.

applied to an extensive panel data set of firms constructed with the help of accounting data for firms belonging to Dutch market services covering the period 1993-1999.

Using a production function approach, we analyse to what extent ICT spillovers matter. Similar to the well-known practice followed for the modelling of R&D spillovers (see, e.g. Jacobs et al., 2002), we construct ICT spillover capital stocks at the industry level. Subsequently, we include this (proximate) spillover indicator in an econometric production function model to capture both the impact of technology spillovers as well as a control for simultaneity or omitted variable biases.

The results of the production function approach will be compared to that of the growth accounting method. Likewise, measured TFP is regressed on the same variables as used in the production function model. This second approach is also conducted to have a comparable method at our disposal as those growth accounting studies at the industry level earlier mentioned.

The plan of the paper is as follows. Section 5.2 discusses the theoretical framework of this paper. Starting with a production function framework, it confronts theoretically two ways of obtaining TFP-measures: via the growth-accounting approach and by estimating a production function. Thereafter, it incorporates ICT technology spillovers and deviations from the perfect-competition case into the analysis. The next Section describes the firm-level data used in the analysis. It gives a precise description of the construction of the balanced panel, the construction of data on capital inputs and the linking of innovation data to the balanced panel. Furthermore, it presents some summary statistics for several key variables. In Section 5.4, we address some econometric issues and explain which estimation method is applied in the empirical part in the next Section. Section 5.5 presents the main results of the production function approach and compares these results with that of the growth accounting approach at different levels of aggregation. Finally, Section 5.6 gives a brief summary and sketches the most important conclusions.

5.2 Theoretical framework

5.2.1 Decomposition of labour productivity growth

Following the general tradition, we start with a production function framework that relates output to input. The production function is approximated by the Cobb-Douglas specification. In logarithmic form this specification reads:

$$y_{it} = a_{it} + \gamma_1 ict_{it} + \gamma_2 k_{it} + \gamma_3 l_{it} \tag{1}$$

where y , *ict*, k and l are the logarithms of respectively real value added (Y), ICT capital (ICT), other capital (K) and labour inputs (L). We use value added as the measure of output as this measure is better comparable across industries than gross output. Subscripts refer to firms (*i*) and years (*t*). The variable a_{it} in (1) represents the log level of TFP. After taking first-differences, we can derive the corresponding equation for TFP growth (denoted by *dTFP*) as:

$$dTFP_{it} \equiv da_{it} = dy_{it} - \gamma_1 dict_{it} - \gamma_2 dk_{it} - \gamma_3 dl_{it} \qquad (2)$$

Equation (2) defines *dTFP* as the growth of output (value added) minus the weighted growth of inputs and uses the production function elasticities as weights. Thus, in essence, TFP growth is a residual (see box). The elasticities needed to implement TFP growth are not directly available and thus have to be estimated in some way. Below we discuss two alternatives: the growth accounting decomposition and the (econometric) production function approach.

TFP growth: a measure of our ignorance
TFP growth in the neoclassical model is assumed to represent exogenous (disembodied) technological change. This assumption disregards that growth-accounting TFP is a catch-all term. Besides exogenous technological change it also covers the contribution of other unspecified inputs, deviations from constant returns to scale and perfect competition and measurement error. TFP growth in the growth accounting method is a residual of output growth that can not be accounted for by the (quality adjusted) traditional input factors. Here, TFP is a proximate cause for economic growth as the growth accounting method does not shed light on the ultimate causes of TFP growth.

Growth-accounting method

The growth-accounting method solves the problem of unknown elasticities by adopting the following assumptions of the standard neoclassical model:

• firms do not have market power in output and input markets (the case of perfect competition);

• the technology is characterised by (global) constant returns to scale (CRS);

• technical change is Hicks neutral and disembodied.

After using these assumptions, the first order conditions of profit-maximising behaviour, stating that marginal costs should be equal to marginal revenue product, imply that the unknown elasticities can be set equal to the observable input shares:

$$\gamma_1 \equiv \frac{\partial Y}{\partial ICT}\frac{ICT}{Y} = \frac{w_{ICT} ICT}{pY} = s_{ICT}^{ga} \qquad (3a)$$

$$\gamma_2 \equiv \frac{\partial Y}{\partial K}\frac{K}{Y} = \frac{w_K K}{pY} = s_K^{ga} \qquad (3b)$$

$$\gamma_3 \equiv \frac{\partial Y}{\partial L}\frac{L}{Y} = \frac{w_L L}{pY} = s_L^{ga}\,, \qquad (3c)$$

where $\{ s_{ICT}^{ga}, s_{K}^{ga}, s_{L}^{ga} \}$ are respectively the cost shares of ICT capital, other capital and labour inputs, $\{ w_{ICT}, w_{K}, w_{L} \}$ is a vector of factor prices for the corresponding inputs and *p* represents the endogenously given output price.

After using the assumption that $s_{ICT}^{ga} + s_{K}^{ga} + s_{L}^{ga} = 1$, equation (2) can be rewritten to obtain an equation for the decomposition of output growth into TFP growth and capital deepening components for ICT capital - and conventional capital inputs respectively:

$$dy_{it} = dTFP_{it}^{ga} + s_{ICT}^{ga} dict_{it} + s_{K}^{ga} dk_{it} + (1 - s_{ICT}^{ga} - s_{K}^{ga}) dl_{it}. \tag{4a}$$

Notice, that the cost shares used in equations (3a) - (3c) are taken relative to total revenue (i.e. value added) and not to total costs. It can be verified that $dTFP_{it}^{ga}$ in (4a) is consistent with a Divisia type index of TFP change (the ratio of a quantity index for one output over the Divisia input quantity index) only, if all firms are faced with perfect competition on all markets and if the technology of each firms can be described by global constant-returns-to-scale (see Balk, 2000).[3] Under these rather restrictive assumptions, the cost shares relative to value added coincide with the shares relative to total costs (TC), where total costs are obtained by adding up labour costs and the user costs of ICT and other capital. These assumptions can be made more explicit by expressing the growth-accounting cost shares as follows:

$$s_{ICT}^{ga} = \frac{w_{ICT} ICT}{pY} = \frac{TC}{pY} \frac{w_{ICT} ICT}{TC} \equiv \mu s_{ICT}^{C},$$

$$s_{K}^{ga} = \frac{w_{K} K}{pY} = \frac{TC}{pY} \frac{w_{K} K}{TC} \equiv \mu s_{K}^{C},$$

$$s_{L}^{ga} = \frac{w_{L} L}{pY} = \frac{TC}{pY} \frac{w_{L} L}{TC} = (1 - \mu s_{ICT}^{C} - \mu s_{K}^{C}),$$

where μ represents deviations from perfect competition and s_{j}^{C} denotes the corrected cost share for input j. In Section 5.2.4 we will discuss the empirical implementation of TFP corrected for deviations from the perfect-competition case in more detail.

[3] In principle, growth rates of output and inputs are measured by Divisia indices. However, since growth rates cannot be observed continuously, they are approximated with the help of Törnqvist weights:
$\bar{v}_{it}^{j} = [s_{it}^{j} + s_{it-1}^{j}]/2$

Production function method

Another way to obtain the unknown production elasticities of (1) is by interpreting equation (4a) as the functional form of a regression model. Replacing the cost shares with the production function estimates obtained after applying some econometric method, then we obtain the production function equivalent of (4a) as:

$$dy_{it} = dTFP_{it}^{e} + \hat{\gamma}_1 dict_{it} + \hat{\gamma}_2 dk_{it} + \hat{\gamma}_3 dl_{it} \tag{4b}$$

where $dTFP_{it}^{e}$ now represents 'estimated' TFP growth based on econometric estimation, i.e. the regression residual of (4b). Note, that (4b) is more flexible than (4a) as it does not impose scale economies and deviations from perfect competition to be absent.

5.2.2 A closer look at the growth accounting approach

Equation (4a) is the empirical device that underlies the majority of growth-accounting studies that were triggered by the ICT-boom of the previous decade. Examples are given in Oulton (2001) for the UK, Pilat and Lee (2001) for OECD countries, Van der Wiel (2001a) for the Netherlands and Vijselaar and Albers (2002) for the Euro Area.

From (4a) it is clear that ICT positively contributes to labour productivity growth if the growth rate of ICT capital exceeds the growth rate of labour inputs. Consequently, the conclusion of growth-accounting studies on industry-level data that ICT investments boost labour productivity growth can be well understood as ICT capital (deepening) significantly increased at this level of aggregation in the 1990s.

As ICT is primarily an investment good for firms, firms will substitute ICT for labour or other types of capital along a given production function if the prices of ICT become relatively cheaper. And they became cheaper than other inputs in the 1990s. So, more and better ICT per worker has contributed to higher productivity. However, it is argued that falling ICT prices are only one part of the story. ICT also has the potential to generate TFP growth due to externalities or excess returns. This implies that the production function of ICT-using industries shifts outward. Here, the evidence at the macro and industry level is scarce.

Growth accounting exercises are, however, principally based on the neoclassical model stating that the contribution of ICT to labour productivity is only channelled through capital-deepening. ICT induces 'normal' rate of returns. These exercises leave no room for a direct assessment of the ICT impact on TFP growth except for the impact of ICT producing industries.[4] To do this in the growth accounting practice requires the use of a two-stage

[4] In that respect, in the late 1990s, the contribution of the latter to TFP growth was considerably in many countries including the Netherlands.

approach, thereby testifying that the impact of ICT on TFP can be isolated from capital deepening. Although, several at the industry level have done that without conclusive answers, a similar approach here is followed at the firm-level by using the measured TFP growth as a dependent variable.

Stiroh (2002) points out that a difference between the estimated ICT output elasticity of (4b) and the ICT cost share of (4a) signals a failure of the neoclassical model to account properly for the distribution of labour productivity growth across the two sources: ICT capital deepening and TFP growth. His argument can be demonstrated by comparing (4a) and (4b). Focussing on ICT capital, this yields:

$$dTFP_{it}^{ga} - dTFP_{it}^{e} = (\hat{\gamma}_1 - s_{ICT}^{ga})dict_{it} + \cdots.$$

This expression shows that a positive 'wedge' between the estimated ICT elasticity and the ICT cost share $(\hat{\gamma}_1 - s_{ICT}^{ga})$ points to a positive correlation between ICT and ('measured') TFP. Furthermore, such a 'wedge' signals an upward bias of measured TFP growth. Notice that this interpretation also rests on the assumed unbiasedness of the ICT capital elasticity. Therefore, a more neutral position would be: a 'wedge' between elasticities and cost shares might mirror two things. Firstly, the benefits of ICT for 'boosting' productivity growth show up in a different way than conjectured by capital deepening. Secondly, this 'wedge' might also be the outcome of using inappropriate model specifications or estimation methods.

Stiroh (2002) offers several economic and econometric explanations why (4a) and (4b) are able to reveal some of the apparent 'proximate' causes behind productivity growth, but at the same time (have to) remain silent on other 'ultimate' causes underlying 'true' productivity relationships (e.g. omission of factors like the contribution of ICT related spillovers, innovation and scale economies). Economic explanations focus on externalities (spillovers) in particular and the econometric 'reasons' concern measurement issues, omitted variables, simultaneity or reversed causality.

Contrary to Stiroh (2002), we elaborate on the before mentioned economic and econometric issues more explicitly along two lines. First, we address the specification problem by extending equation (1) in order to capture the impact of ICT spillovers, deviations from the perfect-competition case and the impact of other innovations on productivity (growth). Second, we apply recently developed estimation methods to the modified model in order to obtain a better control for other potential biases concerning its estimation. More details will be discussed in Section 5.4.

5.2.3 ICT spillovers

The main focus of this paper is whether ICT spillovers matter for TFP growth. This subsection discusses its features. There is a lengthy list of literature that emphasizes how ICT enables the creation and use of network externalities and spillovers. ICT externalities imply that social returns on investment can exceed their private returns because the benefits of computer usage increase when ICT is adopted by more users (the direct network effect).

The increased use of ICT facilitates new organisations of production and sales at the firm level as well as economy wide. At the level of individual firms ICT network externalities are expected to show up in non-pecuniary rents or production efficiency gains arising from the streamlining or upgrading of internal business processes (see, e.g. Black and Lynch, 2000 and Bresnahan et al., 2002) or improved business-to-business communications (see, e.g. OECD, 2003). Furthermore, besides being intrinsically an instance of process innovation itself, ICT may also enable innovation in a broader way, by enhancing the creation of new or better applications (the indirect spillover effects).

These typical characteristics of ICT suggest that an increasing use of ICT predominantly invokes a shift in the production frontier (at the firm level as well as at higher levels of aggregation) rather than a movement along the production frontier as conjectured by the neoclassical model (Bartelsman and Hinloopen, 2000). Moreover, following Van Ark (2002), network externalities also 'justify' why the marginal product revenue of ICT capital can exceed the marginal costs of investing in computers.

So, the potential of ICT to produce production externalities or spillovers simultaneously explains:

- why estimated ICT elasticities obtained from regressions on firm-level data can exceed the ICT cost shares used in the growth-accounting practice
- the other side of the (same) coin: the relatively low contribution of ICT capital deepening to the acceleration of labour productivity growth as extensively documented at the industry or macro level in growth-accounting studies.

Furthermore, the fact that the ICT 'boom' was an economy wide phenomenon also explains some of the problems encountered in regression analysis applied to industry-level data. The latter may have something to do with the failure of econometric studies on aggregated time series data to identify or disentangle the ICT impact from the contribution of technological change in the presence of an economy wide supply shock (e.g. world trade).[5]

[5] The importance of taking into account the 'trending' behaviour of ICT has been demonstrated recently by O'Mahony and Vecchi (2002). Starting with the application of standard (panel) estimation methods to a panel of industry-level data, they could not find any significant impact of ICT on output growth. However, the application of an Error-Correction model yielded very substantial evidence for the contribution of ICT to output growth.

5.2.4 Deviations from the perfect-competition case

As we use TFP (growth) based on growth-accounting at the firm level, another feature of this method deserves further attention. In Section 5.2.1 we mentioned the 'perfect-competition case' as one of the basic assumptions underlying the 'growth-accounting' method. Our data consists for a large part of firms belonging to the (business) services sector, thereby representing a very heterogeneous collection of markets that are mostly characterised by a high degree of product differentiation (see also Kox, 2002). This empirical fact makes it hard to justify that all these markets are 'ruled' by perfect competition. It seems more reasonable to relax this assumption at least for the output markets and to allow these markets to deviate from the perfect-competition case.

Griffith (2001) shows that in case of imperfect competition on output markets the usual measures of TFP growth are likely to be 'biased' and that the direction of the bias depends on changes in input ratios. Following Griffith (2001) and Klette (1999), we control for this 'competition bias' by introducing 'mark-ups'. If a firm has to some extent market power in output markets and remains a price taker in input markets, then the perfect-competition price (*p*) in (3a) - (3c) should be replaced by marginal revenue product (*r*) given by:

$$r_t = p_t(1 - \frac{1}{\varepsilon_t}),$$

where ε_t is the price elasticity of demand. Perfect competition on output markets corresponds with $\varepsilon_t \to -\infty$ or, equivalently, $\mu = 1$. In this paper we allow for deviations from 'perfect competition' on output markets by expressing that the equality of prices and marginal cost is broken down at the market level:

$$\frac{P_t}{MC_t} = \mu_{mt} = (1 - \frac{1}{\varepsilon_{mt}})^{-1}, \text{ with } \mu_{mt} \geq 1.$$

We define a market (indexed by *m*) as a group of firms belonging to the same 3-digit level of NACE. In the empirical application we approximate the 'mark-up' over variable cost with the ratio of prices over average total costs. This has been achieved by using the data on output (value added in current prices) and total costs (the sum of labour, ICT and other capital costs). Thus, we use:

$$\mu_{mt} = \frac{P_{mt}Y_{mt}}{TC_{mt}} = \frac{P_{mt}}{AC_{mt}}$$

to obtain a modified set of expressions for the cost shares to be used in the TFP calculations. For input j this modification yields:

$$\hat{s}_{it}^{j} = \mu_{mt} \frac{w_{it}^{j} X_{it}^{j}}{p_{it} Y_{it}} > s_{it}^{j} ,$$

indicating that the 'measured' cost share of input j relative to value added ($\hat{s}_{it}^{j}$) can be considered as a 'disturbed' estimate of the preferred Divisia input weights (s_{it}^{j}). Stated otherwise, TFP as calculated on the basis of unadjusted cost shares does not represent 'true' technological TFP in case of imperfect competition on output markets.

Possible impact of competition on TFP growth

Using $\mu_{mt} > 1$ we can show how a TFP 'competition-bias' emerges if output markets deviate from 'perfect-competition' and if the technology can be described by global constant-returns-to scale in all inputs. Starting from:

$$TFP_{it}^{ga} = y_{it} - \hat{s}_{it}^{ict} ict_{it} - \hat{s}_{it}^{k} k_{it} - (1 - \hat{s}_{it}^{ict} - \hat{s}_{it}^{k}) l_{it} , \qquad (6a)$$

and using $\hat{s}_{it}^{ict} = \mu_{mt} s_{it}^{ict}$ and $\hat{s}_{it}^{k} = \mu_{mt} s_{it}^{k}$, then (6a) can be rewritten as

$$TFP_{it}^{ga} = TFP_{it}^{cga} - (\mu_{mt} - 1) s_{it}^{k} (k_{it} - l_{it}) - (\mu_{mt} - 1) s_{it}^{ict} (ict_{it} - l_{it}) , \qquad (6b)$$

where TFP_{it}^{ga} denotes TFP according to (standard) 'growth-accounting' and TFP_{it}^{cga} represents its equivalent corrected for the possible competition bias. Furthermore, equation (6b) serves as a starting point for assessing the competition bias of measured TFP growth, as the differencing of (6b) yields:

$$dTFP_{it}^{ga} = dTFP_{it}^{cga} - \bar{v}_{it}^{k} (dk_{it} - dl_{it}) - \bar{v}_{it}^{ict} (dict_{it} - dl_{it}) , \qquad (7a)$$

with Törnqvist weights given by:

$$\bar{v}_{it}^{k} = [(\mu_{mt} - 1) s_{it}^{k} + (\mu_{mt} - 1) s_{it-1}^{k}] / 2 , \text{ and} \qquad (7b)$$

$$\bar{v}_{it}^{ict} = [(\mu_{mt} - 1) s_{it}^{ict} + (\mu_{mt} - 1) s_{it-1}^{ict}] / 2 . \qquad (7c)$$

Equation (7a) shows that the direction of the bias of 'measured' TFP growth is indeterminate in general. However, taking into account the impressive record of ICT investment in the previous decade, it is likely that 'measured' TFP growth underestimated 'true' TFP growth in the period under consideration.

Wrapping up and putting the pieces together, ICT spillovers and deviations from perfect competition lead to two opposing effects on measured TFP growth using the growth accounting:

• ICT spillovers could imply an upward bias of measured TFP growth;
• If markets are non-perfect this could result into an underestimated TFP growth.

Which effect is stronger, is up to empirics.

5.3 Data

5.3.1 The construction of panel data

In the empirical part of this paper we will use a balanced panel consisting of firm-level data for firms belonging to the Dutch service sector. The panel covers the period 1994–1998 and is constructed after linking the detailed accounting data collected in the yearly Production Surveys of Statistics Netherlands over time.

The accounting data cover, among others, the following key variables: gross output, total turnover, employment in full time equivalents (from 1995 onwards) and employed persons[6], intermediate inputs, wage costs (including social security charges), investments, depreciation costs and before-tax profits. The data enable the construction of value added as the measure of output.[7] In order to consider real outputs and inputs in our analyses, we use detailed price indices from the National Accounts to construct value added in constant (1995) prices at lower levels of aggregation.

The panel contains interesting features, but is not completely perfect. Regular issues of sampling, covering, missing variables are at stake. One of the missing variables is that at the level of the firm no prices are available. Likewise, the average size of firms in the balanced panel is considerably higher than actually measured for the total population of firms. The Dutch service sector consists of many small firms and, due to the sampling design, many of them are only occasionally covered in the Production Survey. The sampling probability increases with firm size and firms that have twenty or more persons employed are sampled every year, in principle. Nevertheless these larger firms may also disappear in the course of time because of bankruptcy, merging with other firms etc. Despite these complications, due to a unique firm identifier one can easily construct panel data linking the yearly surveys over time.

---

[6] We use persons employed as the measure of labour inputs because this variable is available in all years.

[7] As mentioned in section 2, we could also opt for gross output (or total sales) as the measure of output, but we have chosen not to do so. The reason for this is that many firms belong to wholesale and retail trade. For these branches the data on intermediate inputs consist for a very large part of purchases on trading goods and this make these data incomparable with the intermediate inputs of other branches.

5.3.2 The construction of capital inputs

Both approaches of Section 5.2 require data on capital stocks. Unfortunately, and common for studies using firm-level data, capital stock data are not readily available and have to be constructed in some way. In this paper, we exploit the interesting feature of the Production Survey that investment data is collected simultaneously with the (other) accounting data.[8] Thus, we have available a consistent set of investment data at the firm level for those firms that are present in every year. This paper distinguishes two types of capital inputs: ICT and other capital. We used the data to construct real expenditures on ICT - and total investment expenditures at the firm-level. For total investment we used National Account price indices at the industry level and for ICT investment we applied the hedonic ICT price index for Germany calculated by Schreyer (2002) to deflate the nominal investment data. The hedonic deflator is used because it better represents the sharp decrease of ICT prices in the previous decade than the corresponding National Accounts price index for computers.

After this, we constructed capital stocks only if we had available at least five consecutive observations on investment in constant prices. Capital stocks for ICT and total capital inputs (including ICT) were constructed by using the perpetual inventory method and assuming constant geometric depreciation (δ_k) for capital of type *k*. Accordingly, the capital stock K_{kt} of type *k* in period *t* reads:

$$K_{kt} = (1-\delta_k)K_{it-1} + I_{kt-1}. \tag{8a}$$

Estimates for the unknown initial levels of the stocks of (9a) were obtained by using the approach of Hall and Mairesse (1995):

$$K_{k1} = \frac{I_{k1}}{g_k + \delta_k}, \tag{8b}$$

in which g_k represents the pre-sample growth rate of real investment for type *k*, and I_{k1} is real investment in the base year.

The implementation of (9a) and (9b) requires a number of assumptions concerning the pre-sample growth of investment and their depreciation. Estimates for g_k were taken from industry

[8] If investment data would have been collected in a separate survey, then the linking of the two surveys would reduce the size of the panel substantially as differences in sampling designs or response rates may complicate the matching. Moreover, as it is now based on one single survey, probably the data are more consistent.

time series and for the depreciation schedule we used values that are close to the parameters underlying the construction of capital stock at the industry level followed by earlier CPB research (van der Wiel, 2001a). The assumed values for g_k and δ_k are summarised in Table 5.1.

Table 5.1 Pre-sample growth of investment (g) and depreciation rates (δ)

	Pre-sample growth		Depreciation	
	Total investment	ICT	Total investment	ICT
Wholesale trade	6.0	25.0	6.5	25.0
Retail trade	6.0	27.5	6.5	25.0
Other services	7.5	20.0	6.5	25.0

Another complication concerning the implementation of (9b) refers to I_{k1}. Contrary to the observable patterns for industry-level data, investment behaviour at the firm level is more erratic. Stated otherwise, investments appear to differ markedly between firms over time. Therefore, the initial capital stock estimates may be too dependent on the probability of having invested in the first year. We circumvent this problem by replacing I_{k1} with the average (real) investment observed in 1994–1998, thereby reducing the influence of firm-specific investment cycles. This approach has been followed for total investment expenditure but not for ICT, for reason that the observed rates of ICT investment were less likely to be dominated by cyclical

Table 5.2 Summary statistics for ICT and total capital inputs for services

	1994	1998
Share of ICT in total capital stock (in prices of 1995)		
Services	1.6	3.3
Wholesale trade	2.6	5.7
Retail trade	0.8	1.7
Business services	1.6	3.4
Other services	0.9	1.0
Growth of capital stocks, 1994 – 1998[a]		
ICT capital		25.5
Total capital		4.5

[a] Annualised growth for total services calculated on the bases of raised totals

fluctuations in the period under consideration.[9]

Table 5.2 reports some summary statistics concerning the construction of capital inputs for the panel data used in the econometric part of this paper. The balanced panel consists of 7828 services firms for which capital stock data could be constructed and that passed through other data cleansing rules.[10] In terms of output (value added in 1996) the balanced panel represents nearly 45% of all firms in the service sector (see Van Leeuwen and Van der Wiel, 2003a, for more details on the construction of the panel). This relatively low coverage ratio is mainly due to the fact that the smallest firms have low inclusion probabilities and, thus, were not surveyed consecutively. However, their contribution to aggregate capital stocks appears to be smaller. In fact, after using the sample weights to obtain results for the whole population, the (weighted) growth rates for capital inputs are similar to those found at the industry level.[11] The table also shows that, although doubled in a short period, the shares of ICT in total capital stocks were still rather small among industries in 1998.

A related complication of the growth-accounting approach is that cost shares of capital inputs have to be constructed. With two inputs (labour and capital) this is easy as the share of capital inputs is the complement of the share of labour relative to value added. However, with two capital inputs, the allocation of non-labour income to ICT and other capital is less straightforward. The usual procedure is to distribute total capital income (value added minus the wage bill) across the two types of capital proportional to their user costs.

5.3.3 Approximating ICT spillovers

In spite of the attention given to ICT spillovers in explaining the value of ICT, their explicit modelling is still in its infancy. The reason for this is obvious. It is hard to imagine how ICT spillovers should be modelled taking into account that ICT has no limits by definition.

As discussed, ICT can generate social returns beyond the private returns flowing to the firms using ICT. These spillovers may show up in different ways. Usually one distinguishes between rent spillovers and technology spillovers. Rent spillovers refer to a situation where the volume of inputs related to the use of ICT capital are higher than measured, due to the fact that real

---

[9] For some firms the share of ICT investment in the first year appeared to be zero and since the econometric specification is in logarithms this raises an additional problem. Omitting these firms may lead to an overestimation of the ICT contribution to output and productivity growth. For this reason we did not exclude these firms but instead we assumed that actual ICT investment was not zero but rounded to zero by the respondents. Accordingly, we imputed for these cases the minimum of ICT investment observed for the sample.

[10]Besides applying a selection rule concerning the requirement of consecutive investment data, we also applied a data cleansing to reject firms with negative values for their value added. However, we did not apply any censoring or trimming of the data to remove firms with extreme values for value added per employee or productivity growth.

[11]The growth rates presented in table 2 are of the same order of magnitude as reported in Van der Wiel (2001a), if one takes into account that the latter study did not use hedonic ICT deflators.

prices are lower than actual prices. This definition can be extended to include the use of non-priced inputs related to ICT use. In this view ICT spillovers enter TFP as an instance of measurement error (see Jacobs et al., 2002). Technology spillovers are linked to the effect that ICT can make it easier to spread new knowledge and absorb it. ICT can induce technological and non-technological innovations.

The fact that ICT is a general purpose technology makes it difficult to implement the theoretical construct of ICT spillovers empirically. In this paper, we assume that ICT mainly generates technology spillovers which show up in better organisational practices within and outside of a firm, thereby enhancing the productivity performance of the firm. One can argue that it makes sense to account for the increased use of ICT outside of the firm as this makes the existing ICT capital stock of a firm more productive.

This output-orientation of ICT spillovers fits reasonably well into the 'primal' representation of technology that underlies the production function framework presented in Section 5.2.1. Similar to Mun and Nadiri (2002) and Jacobs et al. (2002), we implement ICT technology spillovers in the model by constructing an indicator for ICT spillover capital. We do so by subtracting a firm's own ICT capital stock from the industry aggregate. Thus approximate ICT spillover capital for firm *i* belonging to industry *I* in year *t* is obtained as:

$$SICT_{it} = \sum_{j=1, j \neq i}^{N(S)} ICT_{jt}.$$

By extending the approaches with this exogenous variable we assume that ICT spillovers affect the location and the structure of the production frontier bounding the relationship between own inputs and output. Therefore, the extended approaches aim at providing a better characterisation of production possibilities than would be the case if spillovers were excluded (see Kumbhakar and Knox Lovel, 2000).

It goes without saying that this measure is only an approximation for the ICT adoption outside of the firm. In that respect, data on inter-industry dependencies are probably more suitable for the analysis of ICT spillovers. One could, however, argue that ICT spillovers predominantly materialise on the firm level. Thus, firm-level data may not be such a bad starting point for assessing their importance.

5.3.4 Linking innovation data

As differences in innovativeness seem to be a natural candidate for explaining differences in firm performance, we determine which part of the balanced panel was innovative during 1994–1998. This has been achieved by linking the two available waves of the Dutch Community Innovation Survey (CIS) to the balanced panel: CIS 2 covering the period 1994–1996 and CIS

2.5, covering 1996–1998.[12] This innovation panel consists of 1451 firms and includes firms that were covered in both waves of CIS.

The linking of CIS data to the accounting data described above is straightforward in principle, as the innovation surveys and the production surveys use a similar unit of observation and have the same unique identifier. Nevertheless, some shortcomings of CIS complicate an analysis of the links between innovation and firm performance in market services (see Van der Wiel, 2001b). In CIS, small firms are even more under represented and this survey also disregards just started firms. As small and starting firms are considered as an important source of (increasing) innovativeness, the low coverage of these firms in CIS could underestimate the importance of innovation in market services. Despite these shortcomings, CIS-data remain imperative for assessing the role of innovation in explaining differences in productivity (growth).

5.3.5 Productivity performance of Dutch market services

Table 5.3 presents some evidence on productivity measures and inputs for both the complete panels. For the complete panel, the table shows that labour productivity growth for Dutch market services was moderate on average, with annualised growth close to 1.5% in 1994-1998.

Table 5.3 Summary statistics for Dutch market services

	Complete panel (N = 7828)		Innovation panel (N = 1451)	
	mean %	stdev %	mean %	stdev %
Growth rate of [a]				
ICT capital	19.8	38.1	29.3	29.2
Other capital	4.3	3.5	4.0	3.2
Employed persons	3.0	12.3	3.3	13.1
Value added per employee	1.5	12.4	2.5	12.3
TFP growth-accounting	0.7	12.0	1.8	12.1
TFP ‘corrected’ growth accounting	0.9	12.3	2.1	13.3
Levels				
Employment 1994	93.9	677.7	181.3	656.0
Employment 1998	111.2	821.5	206.6	753.2
Value added per employee 1994[b]	38.1	67.9	41.4	29.5
Value added per employee 1998[b]	43.3	69.4	51.3	63.2

[a] Annualised (not weighted) growth rates calculated over the period 1994–1998.
[b] Weighted levels in constant (1995) prices x 1000 Euro.

We also listed statistics for TFP growth based on two growth accounting measures. The first one uses formula (6a) to calculate TFP based on the standard traditional assumption. The second TFP measure uses the same formula, except that the shares are corrected for ‘imperfect competition’ with the help of the market-specific mark-ups. Thus, we use:

[12] Prior to the third wave of the big and harmonised European CIS (CIS 3) Statistics Netherlands has carried out an intervening survey, called Cis 2.5.

$$TFP_{it}^{cga} = y_{it} - \frac{\hat{s}_{it}^{ict}}{\hat{\mu}_{mt}} ict_{it} - \frac{\hat{s}_{it}^{k}}{\hat{\mu}_{mt}} k_{it} - (1 - \frac{\hat{s}_{it}^{ict}}{\hat{\mu}_{mt}} - \frac{\hat{s}_{it}^{k}}{\hat{\mu}_{mt}}) l_{it} \tag{9}$$

to calculate 'corrected' growth-accounting TFP (TFP_{it}^{cga}).

Table 5.3 shows that the contribution of TFP to labour productivity growth varies between 47% and 60% for the two considered measures of TFP based on the complete panel. Furthermore, and in line with the discussion in the previous Section, it is shown that TFP growth increases when deviations from 'perfect competition' are taking into account. Nevertheless, the difference between the 'mark-up' corrected measure of TFP growth and the traditionally measured contribution of TFP growth appears not to be very substantial.

Although the difference between the traditional measure of TFP growth and the corrected TFP growth appears to be not very exiting, the measures of the mark-up are considerably greater than one (see Table 5.4). Moreover, the average 'mark-ups' for services as a whole rose from about 1.23 in 1994 to about 1.27 in 1998.

Table 5.4 Mark-up results in market services, 1994 and 1998

	1994	1998
Complete panel	1.228	1.269
Innovation panel	1.238	1.272

If we compare the results between the balanced panel and the innovation panel in Table 5.3, the most striking difference is that the latter consists of a collection of firms that had a remarkably better productivity performance in terms of labour productivity and TFP than their counterparts (the firms not covered in CIS). For the innovation panel average labour productivity in 1998 was nearly 20% higher than for the complete panel. Furthermore, labour productivity growth was also substantially higher for the innovation panel than the comparable figure for the complete panel (2.5% versus 1.5%). Notice further that productivity growth and firm size seem to be correlated as the 'average firm' in the innovation panel is larger than in the complete panel. Furthermore, the better productivity performance of the innovation panel appears to arise mainly from a higher contribution of TFP growth and irrespective of the measure of TFP growth used.[13]

[13] Again, we obtain the result that correcting for a possible competition bias results in a higher *TFP* growth than in 'standard' growth-accounting.

5.4 Econometric issues

5.4.1 Introduction

This Section discusses several econometric issues concerning the estimation of both approaches (i.e. the production function approach and the growth accounting approach). Before adding the stochastic assumptions to the models, we first have to be clear about the specification of the TFP component. Therefore, Section 5.4.2 comments on issues such as the spillover indicator, innovation, the initial ICT-intensity and unobserved firm characteristics. Section 5.4.3 discusses the econometric estimation method.

5.4.2 Specifying TFP

As mentioned before, our primary interest in this paper concerns the role of ICT production externalities in explaining differences in productivity (growth). Therefore, a first and quite natural step is to 'purify' TFP by using the proximate ICT spillover indicator given by equation (5) of Section 5.2.3.

Although possibly important, ICT externalities may only be one of the many sources of productivity differences between firms. A notorious problem often encountered when estimating production function parameters concerns the role of unobserved firm characteristics. To give an example: one can imagine that firms differ in the skill structure employed as a consequence of ICT usage. If these differences (which typically are positively correlated with size) cannot be taken into account explicitly, then one can expect a correlation between this 'unobservable' and the included explanatory variables. Other examples of unobserved firm characteristics are differences in the (pre-existing) vintage structure of capital inputs or the quality of management.

The usual way to control for these unobserved firm characteristics is to adopt an error component structure. In the empirical application we extend the commonly applied error component model by including additional 'controls' for firm-specific initial conditions that can be implemented which firm-specific observed variables. For each firm we determine its (relative) ICT intensity at the beginning of the period and we use this ICT intensity dummy as a control for the continuous ICT variables that are correlated with initial stocks.[14]

Similarly, we control for an innovation impact on TFP if the model is applied to the innovation panel. We recall that we label a firm 'innovative' if it has applied at least one type of innovation in the period under consideration. Thus, we use an innovation dummy variable to capture the contribution of innovation to TFP. We are forced to the use such a qualitative variable due to the lack of continuous and more informative variables in CIS for market

[14] The ICT intensity dummy variable has been constructed as follows. For each NACE 3-digit we determined the median score of the share of ICT capital in the total capital stock for 1994. Thereafter we assigned a value of one to the ICT dummy if the firms' score was above the corresponding median value. This firm is labelled as ICT intensive. Low ICT-intensive firms are the reference group.

services. A more precise account for innovation is not possible, because the data do not contain information on innovation output for most of the firms that implemented technological innovations. Furthermore, data on innovation costs incurred are not available for the many firms that implemented non-technological innovation only.

Summing up, this leads to the following specification for TFP in (1):

$$a_{it} = \gamma_4 sict_{it}^I + \alpha_i + \sum_{s=1}^{S} \lambda_s D_s t + \beta_1 D_{i,ICT} + \beta_2 D_{i,Inno} + \nu_{it} \tag{10}$$

In (10) $sict_{it}^I$ is the logarithm of ICT spillover capital and α_i a firm-specific fixed effect that may be freely correlated with all other variables of the estimating equation. The third term on the right-hand side of (10) represents the contribution of disembodied technical progress, which is assumed to vary between industries. The following common breakdown of market services is used for the constructing the industry dummy variables of (10):

• Wholesale trade (reference industry, trade and repair of cars excluded, NACE-code 51);
• Retail trade (trade and repair of cars excluded, NACE-code 52);
• Business services (NACE-code 71-74);
• Wholesale -, retail trade and repair of cars (NACE-code 501-505);
• Other business services (NACE-code 55, 90).

Furthermore, $D_{i,ICT}$ and $D_{i,Inno}$ are dummy variables that are included to capture the contribution of initial conditions concerning a firm's ICT intensity and the contribution of innovation to TFP, and ν_{it} represents the remaining transitory and idiosyncratic differences in productivity. Putting the pieces together for both approaches, after inserting (10) in (1) for *the production function approach*, it follows that:[15]

$$y_{it} = \gamma_1 ict_{it} + \gamma_2 k_{it} + \gamma_3 l_{it} + \gamma_4 sict_{it}^I + \alpha_i + \sum_{s=1}^{S} \lambda_s D_s t + \beta_1 D_{i,ICT} + \beta_2 D_{i,Inno} + \nu_{it}, \tag{11a}$$

and for the *growth-accounting approach*

$$TFP_{it}^{cga} = \tilde{\gamma}_1 ict_{it} + \tilde{\gamma}_2 k_{it} + \tilde{\gamma}_3 l_{it} + \tilde{\gamma}_4 sict_{it}^I + \tilde{\alpha}_i + \sum_{s=1}^{S} \tilde{\lambda}_s D_s t + \tilde{\beta}_1 D_{i,ICT} + \tilde{\beta}_2 D_{i,Inno} + \tilde{\nu}_{it}, \tag{11b}$$

[15] Equation (10) is the most extended specification of TFP and can be applied to the innovation panel only. If we use the complete panel than the innovation dummy variables are not included in the model.

in which TFP_{it}^{cga} is calculated according equation (8).[16]

The estimation of the (enhanced) production function approach (11a) aims at minimising the risk of simultaneity or omitted variables bias for the traditional inputs in order to obtain better estimates for TFP (growth). Estimating specification 11b tests the potential ultimate sources using the measured (growth-accounting) TFP.

A similar approach as applied in the growth accounting approach could be followed for the production function approach by using the residual $dTFP_{it}^{e}$ obtained after applying OLS to (4b) as the starting point. However, viewed from an econometric perspective, this route is not preferable if there are reasons to assume that the TFP component of labour productivity growth is related to ICT too. Then, the estimates of (4b) may suffer from an estimation bias. In particular, the latter reason might explain why studies on the firm level obtained higher ICT elasticities than seems to be consistent in view of the (still) relatively low cost shares of ICT.

A comparison of the results of model (11a) with or without ICT spillovers enables us to judge whether the estimates of ICT capital stock elasticities are 'hiding' an ICT impact on TFP (growth). Finally, estimating (11a) and (11b) as well also provide a benchmark for TFP-regressions carried out in growth-accounting studies at the industry level. These studies show up to be inconclusive with respect to the contribution of ICT to TFP growth (see, e.g. Van der Wiel, 2001a, and Stiroh, 2002).

5.4.3 Estimation methods

In equations (11a) and (11b) we have included firm-specific fixed effects as separate parameters which only vary between firms. These parameters can be eliminated by estimating the models in growth rates. For production function (11a) this yields:

$$\Delta y_{it} = \alpha + \gamma_1 \Delta ict_{it} + \gamma_2 \Delta k_{it} + \gamma_3 \Delta l_{it} + \gamma_4 \Delta sict_{it}^{I} + \sum_{s=1}^{S-1} \lambda_s D_s + \Delta \nu_{it} \tag{12a}$$

whereas for the growth-accounting approach (11b) we use:

$$\Delta TFP_{it}^{cga} = \tilde{\alpha} + \tilde{\gamma}_1 \Delta ict_{it} + \tilde{\gamma}_2 \Delta k_{it} + \tilde{\gamma}_3 \Delta l_{it} + \tilde{\gamma}_4 \Delta sict_{it}^{I} + \sum_{s=1}^{S-1} \tilde{\lambda}_s D_s + \Delta \tilde{\nu}_{it} \, . \tag{12b}$$

However, this transition from the cross-sectional dimension to the time series dimension of the data may not solve all problems. Reversed causality and measurement errors may still cloud results. If productivity shocks are anticipated before factor demands are determined, than

[16] We add a tilde to the parameters of the TFP model in order to make a distinction between the parameters of the production function model and the TFP model.

changes in productivity shocks ($\Delta\nu_{it}$) remain correlated with the right-hand side variables of the equations and this may bias estimates upwards. On the other hand, we have to face the consequences that measurement problems may be exacerbated when estimating the model in first-differences, thereby giving rise to a downward estimation bias which may completely offset the positive 'causality' estimation bias. Indeed, with the data at hand and the method chosen for constructing capital inputs, errors-in-variables are very likely cause of correlations between $\Delta\nu_{it}$ and the capital inputs.

SYS-GMM provides an optimal way to combine the orthogonality conditions (see box and, particularly formula (13a) and (13b)). In the empirical application we will apply this method by using the full set of conditions given by (13a). From (13b) we use the conditions that cover all valid instruments for the level equation pertaining to 1998. Thus, when estimating production function parameters, the system uses equation (12a) for 1996, 1997 and 1998 and equation (11a) for 1998.[17]

The SYS-GMM estimator

The usual way to account for a possible correlation between the error of the models (12a) or (12b) and the explanatory variables is to use the GMM estimator (see for example Mairesse and Hall, 1996). This generalised instrumental-variables estimator uses the following orthogonality conditions[a]

$$E[\nu_{it}\Delta X_{i,t-s}] = 0 \text{ for } t = 3, \ldots, T \text{ and } 2 \leq s \leq t-1. \tag{13a}$$

These conditions exploit the lagged explanatory variables of the level equation (11a) as instrumental variables after the equation has been differenced to eliminate the unobserved fixed effects. However, the resulting first-difference estimator often appeared to give unsatisfactory results (see, e.g. Blundell and Bond, 1998a). Typical examples for the production function framework showed that capital elasticities were implausibly low and often insignificant when using GMM estimation. These problems are related to the weak correlation that can exist between growth rates of the inputs and the lagged levels of these variables. For instance, since capital stocks within firms are highly persistent over time, one may expect that the correlation between the current growth rate and lagged level of the capital stock is close to zero (see Hempell, 2002, for an illustration).

Blundell and Bond (1998b) showed that the performance of GMM estimators can be improved considerably by exploiting the so-called SYS-GMM estimator of Arellano and Bover (1995). This estimation strategy uses both the equations in first-differences (e.g. (12a), instrumented with 'levels') and the equations in levels (e.g. (11a), instrumented with 'first differences') simultaneously, thereby imposing cross-equations constraints for the parameters of interest. This is achieved by extending the set of orthogonality conditions with

$$E[\nu_{it}\Delta X_{i,t-1}] = 0 \text{ for } t = 3, \ldots, T. \tag{13b}$$

and by stacking (13a) and (13b) to obtain a system.

[a] The vector X collects the explanatory variables of equation (11a).

---

[17] Using only the level equation in 1998 is sufficient if the method is applied to balanced panel data (see Arellano and Bover, 1995). In this case $(\Delta X_{1995},\ldots,\Delta X_{1997})$ are valid instruments.

5.5 Results

5.5.1 Results of production function approach[18]

We begin the presentation of the estimates by first looking at the econometric estimates for the production function approach using a traditional Cobb-Douglas specification. To obtain a link with other studies based on firm-level data (e.g. Brynjolffson and Hitt, 1995) we first used (11a) and (12a) without taking into account the contribution of innovation and the impact of initial ICT adoption on TFP.

Table 5.5.1 SYS-GMM results for the production function approach for service firms[a]

	Complete panel		Innovation panel	
	A	B	C	D
N	7828	7828	1451	1451
ICT capital (γ_1)	0.077	0.029	0.046	0.025
	(0.006)	(0.007)	(0.011)	(0.009)
Other capital (γ_2)	0.122	0.144	0.119	0.177
	(0.024)	(0.046)	(0.058)	(0.051)
Labour (γ_3)	1.034	0.964	0.545	0.543
	(0.044)	(0.042)	(0.079)	(0.066)
ICT spillover capital (γ_4)	X	0.079	X	0.131
		(0.035)		(0.049)
ICT intensity (β_1)	X	0.034	X	0.037
		(0.046)		(0.055)
Innovation (β_2)	X	X	0.289	0.273
			(0.051)	(0.048)
Scale parameter[b]	[0.233]	[0.137]	[-0.290]	[[-0.254]
	(0.022)	(0.031)	(0.078)	(0.071)
R^2	0.81	0.85	0.74	0.75

[a] The dependent variable is value added in constant prices (1995). All regressions control for first - and second order correlation in the error term of the models. Robust standard errors of the estimates are presented in parenthesis.
Column A refers to production function approach without ICT spillovers and the (initial) ICT intensity and innovation impact on the TFP level. Column B includes ICT spillovers and the ICT intensity dummy in the baseline model. Column C is the same model as A but now applied on the innovation panel and column D extends model C by also including the impact of innovation conditions on TFP levels.
[b] The scale parameter is derived afterwards with the help of the estimated elasticities of ICT capital, other capital and labour.

[18] The presentation of estimates will be restricted to the results of the SYS-GMM estimation method. The appendix compares this method with standard GMM and discusses the validity of the additional moment restrictions employed. This comparison shows that SYS-GMM yields more reasonable values for the estimated capital elasticities with higher precision.

Column (A) of Table 5.5.1 presents the results for the production function approach without spillovers and initial ICT conditions using the complete panel, covering all firms in the Dutch market service sector. The table shows that all estimates (including the capital elasticities) are significantly different from zero. The outcome for the ICT capital stock elasticity is close to 0.08. Estimates of a comparable magnitude were also reported by Brynjolffson and Hitt (1995) and Hempell et al. (2002).

This result reaffirms that the ICT impact on output growth (and labour productivity growth) can be identified reasonably well when using firm-level data. The relatively high estimate for the ICT capital stock elasticity underlines the importance of ICT capital deepening for labour productivity growth. Taking into account the growth rate of ICT capital stock per employee (see Table 5.3), the point estimate would even imply that (on average) all productivity growth came from ICT capital deepening.

The next phase in our analysis is to specify and break down the TFP variables, consisting of ICT spillovers, the initial conditions concerning the initial ICT intensity and innovativeness. We do this in three steps and the results of these steps are reported in Table 5.5.1 under column B to D respectively. Again, and to enhance a better comparison, we start with the data of the complete panel. Therefore, we will not account for an innovation impact on TFP levels at this stage.

Column (B) of Table 5.5.1 summarises the results for the full model (11a) and (12a) with ICT spillovers and the initial conditions concerning the initial ICT intensity included. The most striking result is that when ICT spillovers are taken into account more explicitly, the elasticity estimate of own ICT capital stocks is lowered substantially. As the estimate of ICT spillover capital is significant, this illustrates that a considerable part of the ICT impact on labour productivity growth is probably channelled through TFP. As a consequence, we obtain an estimate for ICT capital which is close to the average ICT cost share. This suggests that controlling for the possibility of simultaneity arising from the correlation between own ICT capital stocks and the (firstly omitted ICT spillover stocks) makes much sense. Furthermore, firms that were relatively ICT intensive in 1994, appear to have higher TFP levels in 1998 than ICT extensive firms, although this effect is not statistically significant.

The next two steps aim at controlling for productivity differences that are related to innovativeness and ICT spillovers. Being innovative can be such a condition, and for this reason we re-estimated the enhanced production function for the firms of the innovation panel. We recall, that average size for this selection of firms was larger than (average) size observed for the complete panel. Furthermore, as also shown in Section 5.3.4, their productivity performance appeared to be slightly better than the average outcome for all firms. In view of these differences one could also expect quite different results for the production function estimates.

Columns (C) and (D) in Table 5.5.1 show the estimation results for the innovation panel. A comparison with the estimates for the complete panel (columns (A) and (B)) reveal that the differences are minor, except for labour inputs. Again, the 'own' ICT capital stock elasticity appears to be lower after the ICT spillover indicator has been included and the elasticity estimate for ICT spillover capital remains significant, even after controlling for an innovation impact on TFP.

A notable difference between the complete panel and innovation panel concerns the scale parameter. According to the corresponding estimate, the null-hypothesis of CRS is rejected convincingly in favour of increasing-returns-to-scale for the complete panel. In contrast, the lower elasticity of labour inputs causes that the CRS-hypothesis is rejected in favour of decreasing-returns-to scale when using the innovation panel. This asymmetric result reflects the importance of scale economies for boosting labour productivity growth in the services sector (see Kox, 2002). Moreover, it suggests the existence of optimal scale sizes in the service sector (see Kox et al., 2003).

Another notable result concerns the contribution of innovation to TFP. The remarkably better productivity performance of innovative firms reported in Section 5.3.4 clearly shows up in the estimates for the contribution of innovation to TFP. According to the estimates presented in columns (C) and (D) of Table 5.5.1, the TFP level of innovative firms was about 28% higher than TFP for non-innovating firms.

5.5.2 Results of growth accounting approach

In this Section we discuss the results for the growth accounting approach that use the corrected TFP as the dependent variable. Using (11b) and (12b) we can directly assess the contribution of ICT to TFP (growth) derived from the two-stage approach underlying the growth-accounting practice.

As discussed, this exercise resembles the econometric attempts to find an ICT impact on TFP of growth-accounting studies. Doing so, we attain a comparable benchmark with earlier studies at higher levels of aggregation. Two differences should be kept in mind. First, here we first constructed an adjusted TFP measure (free from competition biases) and, thereafter, applied the SYS-GMM method to explain simultaneously differences in TFP levels and TFP growth. Second, our attempt is conducted at the level of the firm. Evidence from industry level studies cannot be used unconditionally to extrapolate the spillover effects on lower levels of aggregation and vice versa.

Table 5.5.2 presents the results of this second approach. First we look at the outcome for the complete panel by comparing the first column of Table 5.5.2 with column (B) of Table 5.5.1. The most striking result is that the estimate for the own ICT capital stock elasticity of Table 5.5.2 is very close to the spillover elasticity of Table 5.5.1. The (very) significant elasticity of own ICT capital reflects the ICT impact on measured TFP in growth accounting practices as predicted by Stiroh (2002). On the other hand, the ICT spillover elasticity for the complete panel appears to be minor and also insignificant. These results suggest that the impact of own ICT investment shows up in different ways than in Table 5.5.1 as a consequence of the two-stage approach adopted in the growth accounting practice. With this we mean that the valuation of ICT capital used for the construction of TFP disregards the value of production externalities that are related to the complementarity of own ICT use and the ICT adoption outside of a firm. Similarly, we find a very significant TFP elasticity of labour inputs in Table 5.5.2. This estimate is significantly positive, pointing to a sizable and positive scale effect on TFP, and this reflects the other side of the same coin as presented by the significant scale parameter of Table 5.5.1.

Table 5.5.2 SYS-GMM results for the growth accounting approach for service firms[a]

	Complete panel	Innovation panel
N	7828	1451
ICT capital (γ_1)	0.070	0.021
	(0.009)	(0.014)
Other capital (γ_2)	-0.189	-0.212
	(0.054)	(0.122)
Labour (γ_3)	0.306	0.142
	(0.052)	(0.119)
ICT spillover capital (γ_4)	0.005	0.097
	(0.040)	(0.067)
ICT intensity (β_1)	0.007	0.253
	(0.057)	(0.114)
Innovation (β_2)	X	0.703
		(0.106)
R^2	0.65	0.72

[a] The dependent variable TFP is calculated with the help of (8), thus the model uses TFP after accounting for the 'competition bias'. Otherwise, note a of Table 5.5.1 also applies to this table.

The last column of Table 5.5.2 presents the estimates for the TFP model for the innovation panel. Again, ICT appears to contribute to TFP growth, but in this model the impact of ICT spillovers is more sizable than the elasticity estimate of own ICT capital stocks. Moreover, and similar to column (D) of Table 5.5.1, we find a very significant innovation impact on TFP. This latter result reaffirms the importance of innovation for explaining differences in TFP. However, the difference between column D of Table 5.5.1 and the result of the last column of Table 5.5.2, should be interpreted with care, as the estimate of Table 5.5.2 has been obtained in a two-stage approach, thereby neglecting a possible correlation between innovation and other inputs. The two-stage approach also leads to strange results for the impact on TFP of initial ICT adoption (a significantly negative estimate for the innovation panel) and for other capital (a negative contribution for both samples).

Summing up: the evidence of Tables 5.5.1 and 5.5.2 seems to underline that ICT spillovers are an important source of TFP growth. Taken on the whole, and focussing on ICT, our finding also corroborates the 'growth-accounting' studies that showed a relatively small – but positive – contribution of ICT capital deepening to labour productivity growth for ICT using industries. Notice however, that this result has been obtained in this study after taking into account ICT spillovers more explicitly.

Viewed from an econometric angle, the production function approach yields more significant and plausible results than the growth accounting approach. It has been found that taking into account differences in levels and growth rates simultaneously, seems to pay off in terms of more reasonable and more precise estimates of the capital deepening parameters.

5.5.3 Decomposing labour productivity growth

In this Section, we compare the decomposition of labour productivity growth following from the econometric approach with the growth-accounting calculations. In more detail, we compare TFP growth derived from the traditional' growth-accounting calculations with 'growth-accounting' TFP growth after the correction for deviations from 'perfect competition', and also the 'direct' calculations of TFP growth obtained from regression analysis of the production function approach. Using the econometric elasticity estimates of ICT and other capital and their geometric averages growth rates derived TFP growth in a similar way as is applied in the 'growth accounting' practice. Doing so, we achieve that the productivity effects of ICT externalities, scale economies and innovation are attributed to TFP (growth).

Table 5.5.3 shows that, after controlling for ICT externalities via the ICT spillover indicator employed, the contribution of ICT capital deepening according to the econometric approach is very similar to the results of the growth-accounting when using the complete panel. For this data set ICT capital deepening shows up to be twice as important for labour productivity growth than was other capital deepening.[19] This conclusion also applies to the selection of innovative firms (the firms that stated to have implemented innovations during the whole period considered). For both samples, we obtained a contribution of ICT capital deepening to labour productivity growth which seems to be rather robust taking into account the two rather different samples.

The most striking result is that the contribution of ICT capital deepening to labour

[19] We recall that the decomposition of labour productivity growth for the two 'growth-accounting' variants presented in table 5.5.2 remains based on the (possibly invalid) assumption of constant returns to scale. Hereafter, we will return to this subject.

productivity growth varies between 30% and 35% and that most of the contribution of ICT is channelled via ICT spillovers. The latter result came already apparent from the estimates of Tables 5.5.1 and 5.5.2. In Table 5.5.3 this is shown more explicitly: the contribution of ICT spillovers to TFP and labour productivity growth varies between 1.5% for all firms and 2.7% for innovators. Especially, the latter seems to be at odd. However, this relatively large contribution is fairly consistent with findings of Munn and Nadiri (2002). They analyse the importance of ICT rent spillovers at the industry-level model with the help of inter-industry commodity flows to analyse the impact of forward and backward linkages of ICT adoption in a cost function framework. In their study they find an elasticity of total costs with respect to ICT spillovers which varied between 2% and 3% for UK market services.

Table 5.5.3 Decomposition of labour productivity growth using firm-level data 1994-1998[a]

	'Growth-accounting'		'Production function'
	Traditional TFP	TFP corrected for 'competition bias'	
	Annualised growth (%)		
Complete panel (N = 7828)	1.5	1.5	1.5
Contribution of:			
ICT capital deepening	0.5	0.4	0.5
Other capital deepening	0.3	0.2	0.2
TFP growth	0.7	0.9	0.8
Of which: ICT spillovers	NA	NA	1.5
Economies of scale	NA	NA	0.4
Rest	NA	NA	-1.1
Innovation panel (N = 1451)	2.6	2.6	2.6
Contribution of:			
ICT capital deepening	1.0	0.7	0.8
Other capital deepening	-0.3	-0.4	0.0
TFP growth	1.9	2.3	1.8
Of which: ICT spillovers	NA	NA	2.7
Economies of scale	NA	NA	-0.6
Rest	NA	NA	-0.3

[a] Contributions calculated on the basis of geometric averages; NA = not applicable.

Table 5.5.3 also sheds some light on the importance of scale economies in market services. The result for the scale parameters of Table 5.5.1 shows up in a contribution of 0.4 % (about 25% of labour productivity growth) if we use the most extended sample. However, for the selection of innovators we have a negative contribution of diseconomies of scale to labour productivity growth of the same order of magnitude. As innovating and size are positively correlated, this suggests the existence of a trade off between innovation and scale economies. As an analysis of this trade off is beyond the scope of this research, this result opens opportunities for further research.

5.6 Conclusions and further research issues

This paper presents an in-depth analysis of the ICT contribution to labour productivity growth in Dutch ICT using industries at the firm level covering the period 1993-1999. It disentangles the impact of ICT on productivity labour productivity growth into a capital deepening effect and a spillover effect by using an ICT-spillover indicator. Additionally, the impact of innovation is accounted for in an innovation panel.

The paper primarily focusses on the impact of ICT usage in Dutch market services. We constructed a balanced panel of firm-level data pertaining to the Dutch service sector in order to investigate the importance for boosting productivity growth of own investment in ICT in a period that was characterised by an economy wide acceleration of ICT investment. It is shown that the boosting of ICT investment at the firm level in response to an economy wide supply shock raises difficulties for the assessment of the contribution of own ICT to the contribution of labour productivity growth.

By using a production function approach, we have found that ICT spillovers can be an important source of TFP growth in ICT-using industries and that controlling for ICT spillovers lowers the elasticities of ICT capital. A further decomposition of TFP growth shows that the ICT spillovers as well as scale economies were probably important sources of labour productivity growth in the period considered. Our results suggest that neglecting ICT spillovers at the firm level entails the risk of an inappropriate allocation of ICT impacts across 'capital deepening' and TFP. This conclusion is reaffirmed if we control for the possibility of an innovation bias in the estimates (that is by re-estimating the models for the innovation panel) and after allowing for deviations from the 'perfect-competition' case.

Our results indicate that, after controlling for ICT externalities via an approximate ICT spillover indicator, the contribution of ICT capital deepening according to the production function approach is very similar to the results of the growth-accounting practice. Nevertheless, the latter approach is not able to disentangle the causes of TFP-growth into ultimate causes like productivity growth arising from ICT spillovers. On average about one third of labour productivity growth in Dutch market services can be attributed to own ICT capital deepening. However, this contribution appears to be less important than the more indirect contribution of ICT spillovers to productivity growth.

We conclude by mentioning two topics for further research. First, in this paper we have tried to account for the importance of deviations from perfect competition, innovation and economies of scale for the explanation of differences in productivity growth. Each of these determinants is capable of explaining (some of the) differences in productivity performance. However, they may not be independent causes. Ample research suggests that innovation and size are positively correlated. However, the relation between innovation and competition is less clear. Future CPB research will try to shed more light on the relation between competition, innovation and productivity.

The second topic for further research concerns the ICT spillover indicator. Here, we have made an attempt to construct and quantify the effect of ICT spillovers at the firm level for the Netherlands and the results seem to be very promising. As far as we know, this is a novelty at this level of aggregation. However, two comments should be considered. First, due to a lack of data availability, the applied spillover indicator is only an approximation. Further research is needed whether an extension of the approximation is achievable and to check whether the presented firm-level results are robust on higher levels of aggregation. Second, besides the main topics of this contribution, ICT and innovation, human capital is an important source of labour productivity. Investments in education and training lead to the accumulation of knowledge and skills. Therefore, an increase of human capital positively affects labour productivity growth. As human capital, ICT and innovation are strongly interrelated, neglecting one of these productivity determinants could lead up to an overestimation of the effect of the included determinants in a regression. Unfortunately, Statistics Netherlands hardly collects any measure of human capital at the firm level.

References

Arellano, M., and O. Bover, 1995, Another Look at the Instrumental Variable Estimation of Error-Components Models, Journal of Econometrics, 68, pp 29-51.

Ark, B. van, 2002, Measuring the ‘New Economy’: An International Comparative Perspective, Review of Income and Wealth, Series 48 (1).

Ark, B. van, R. Inklaar and R.H. McGuckin, 2003, ICT and productivity in Europe and the United States: where the differences come from, May.

Balk, B.M., 2000, Divisia Price an Quantity Indices: 75 Years After. Mimeo Department of Statistical Methods, Statistics Netherlands.

Bartelsman, E.J. and J. Hinloopen, 2000, De verzilvering van een groeibelofte, in ICT en de economie, Koninklijke Vereniging voor Staathuishoudkunde, Preadviezen 2000.

Berndt, E.R. and C.J. Morisson, 1995, “High-Tech Capital Formation and Economic Performance in U.S. Manufacturing Industries: An Exploratory Analysis, Journal of Econometrics, vol. 65, pp. 9-43.

Black, S.E. and L.M. Lynch, 2000, What’s driving the new economy: the benefits of workplace innovation, NBER Working Paper series No. 7479, January 2000.

Blundell, R. and S. Bond, 1998a, GMM Estimation with Persistent Panel Data: an Application to Production Functions, Working Paper Series No. W99/4, Institute for Fiscal Studies, London.

Blundell, R. and S. Bond, 1998b, Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, Journal of Econometrics, vol. 87, pp. 115-143.

Bresnahan, T. F., E. Brynjolfsson and L.M. Hitt, 2002, Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence, Quarterly Journal of Economics, vol. 117, pp. 339-376.

Broersma, L., R.H. McGuckin and M.P. Timmer, 2002, The impact of computers on productivity in the trade sector: Explorations with micro data, Research paper University of Groningen.

Brynjolfsson, E., and L.M. Hitt, 1995, Information Technology As A Factor Of Production: The Role of Differences Among Firms, Economics of Innovation and New Technology, vol. 3, pp. 183-199.

Brynjolfsson, E., and L.M. Hitt, 2000, Beyond Computation: Information Technology, Organizational Transformation and Business Performance, Journal of Economic Perspectives, vol. 14, pp. 23-48.

Gordon, R.J., 2000, Does the ‘New Economy’ measure up to the great inventions of the past?, Journal of Economic Perspectives, Vol. 14, no.4, pp. 49-77.

Griffith, R., 2001, Product market competition, efficiency and agency costs: An empirical analysis, IFS, WP 01/12, Institute for Fiscal Studies, London.

Hall, B.H., and J. Mairesse, 1995, Exploring the relationship between R&D and productivity in French manufacturing firms, Journal of Econometrics, vol. 65(1), pp. 263-293.

Hempell, T., 2002, What’s spurious, What’s real? Measuring the productivity impact of ICT at the firm-level, ZEW Discussion Paper 02-42, Centre for European Economic Research, Mannheim. (ftp://ftp.zew.de/pub/zewdocs/dp/dp0242.pdf).

Hempell, T., G. van Leeuwen and H.P. van der Wiel, 2002, ICT, innovation and business performance in services: evidence for Germany and the Netherlands, OECD, DSTI/EAS/IND/SWP/AH(2002)7.

Jacobs, B., R. Nahuis and P.J.G. Tang, 2002, Sectoral Productivity Growth and R&D Spillovers in the Netherlands, De Economist, vol. 159, no 2, pp. 181-210.

Jorgenson, D.W., and K. J. Stiroh, 2000, Raising the Speed Limit: U.S. Economic Growth in the Information Age, Brookings Papers on Economic Activity, pp. 125-211.

Klette, T.J., 1999, Market power, scale economies and productivity: estimates from a panel of establishment data, Journal of Industrial Economics, vol XLVIII no 4, pp. 451-476.

Kox, H.L.M., 2002, Growth challenges for the Dutch business services industry; international comparison and policy issues, Special study No. 40, CPB, The Hague.

Kox, H.L.M., G. van Leeuwen and H.P. van der Wiel, 2003, Scale effects on business services; an international comparison, CPB Discussion paper (forthcoming).

Kumbhakar, S.C. and C.A. Knox Lovell, 2000, Stochastic Frontier Analysis, Cambridge University Press, Cambridge UK.

Leeuwen, G. van, and H.P. van der Wiel, 2003, Relatie ICT en productiviteit: Een analyse met Nederlandse bedrijfsgegevens, CPB memorandum no 57.

Mairesse, J. and B.H. Hall, 1996, Estimating the Productivity of Research and Development in French and US Manufacturing Firms: an Exploration of Simultaneity Issues with GMM Methods. In Wagner, K. and B. Van Ark (eds.), International Productivity Differences and Their Explanations, Elsevier Science, 285-315.

Mun, S-B and M.I. Nadiri, 2002, Information technology externalities: empirical evidence from 42 U.S. industries, NBER Working Paper 9272, October 2002.

OECD, 2003, Seizing the benefits from ICT- an international comparison of the impacts of ICT on economic performance, DSTI/IND/ICCP(2003)2.

O'Mahoney, M. and M. Vecchi, 2002, In search of an ICT impact on TFP: Evidence from industry panel data, NIESR, October 2002.

Oulton, N., 2001, ICT and productivity growth in the United Kingdom, Working Paper No. 140, Bank of England.

Pilat, D. and F. Lee, 2001, Productivity Growth in ICT-producing an ICT-using Industries: A Source of Growth Differentials in the OECD?, STI Working Paper 2001/4, OECD, Paris.

Schreyer, P., 2002, Computer prices and international growth and productivity comparisons, Review of Income and Wealth, vol. 48, no 1, pp.15-31, March 2002.

Stiroh, K.J., 2002, Are ICT spillovers driving the New Economy? Review of Income and Wealth, Vol. 48, no 1, March 2002.

Vijselaars, F. and R. Albers, 2002, New technologies and productivity growth in the Euro area, European Central Bank, Working Paper Series No. 122, February 2002.

Wiel, H.P. van der, 2001a, Does ICT boost Dutch productivity growth?, CPB Document no 016.

Wiel, H.P. van der, 2001b, Innovation and productivity in services, CPB Report 2001/1, pp 29-36.

Appendix 5.1 Validity of SYS-GMM model

Short introduction

Here, we test the validity of using the SYS-GMM-model in this paper. In the GMM method the first differenced equations of the model are 'instrumented' with the help of (lagged) levels of the explanatory variables. The extended GMM-method (i.e. SYS-GMM also uses the level equations of the model and use first differences of the same explanatory variables as the instrumental variables. This extension of the traditional GMM method aims at exploiting also the information contained in the cross-sectional differences of levels of the variables included in the model.

In both cases the GMM-method exploits the panel data structure by making use of the additional moment restrictions that become feasible in the course of time. Contrary to the standard IV-estimator, GMM-methods allow the projections on the instruments to be different for every year. In principle, this yields better predictions for the endogenous explanatory variables in finite samples and hence smaller standard errors for the estimated coefficients. However, in spite of this advantage, the inclusion of longer lags of explanatory variables as additional instrumental variables may not yield additional efficiency gains (more precise estimates) by definition when the additional instruments are highly correlated with the instrumental variables already included.[20]

Testing for the validity of additional moment restrictions

The usual way to investigate the validity of (additional) moment restrictions is by using the Sargan/Hansen test. In the sequel we will employ the so-called 'incremental' version of this testing procedure. Under the null hypothesis that all additional moment restrictions hold, the 'incremental Sargan' test statistics is chi-squared distributed with degrees of freedom (DF) equal to the number of the additional moment restrictions employed.[21] This testing procedure has been applied to the production function models estimated for the innovation panel (columns C and D of Table 5.5.1 of the main text). The results are summarised in Table 5A.

The baseline model (A), labelled GMM(-2), uses lag two and earlier levels of the explanatory variables as instrumental variables. This specification allows for simultaneity of the three capital stocks (own ICT capital, own stocks of other capital inputs and ICT spillover capital) at the beginning of each period by dropping the instrumental variables contained in X_{t-1}.

Next, we re-estimated this model after including X_{t-1} as additional instrumental variables (see entry B of Table 5A). It can be seen that the 'incremental Sargan' test rejects the validity of the additional set of instrumental variables.[22] With the exception of the estimate of labour inputs the estimated coefficients of the two models appear to be very similar, as are there standard errors. The low estimate for labour inputs signals that the measurement-error bias seems to exceed the counteracting simultaneity bias when also (invalidity) using 'lag one' instruments.

[20] In Mairesse and Hall (1996) it is shown that GMM methods still (can) perform better than the standard IV method in this case, because of the different sets of instrumental variables applied for different equations and not because of using more instrumental variables as such.

[21] If we have k parameters to estimate and use J_1 ($J_1 > k$) moment restrictions, then the standard Sargan test procedure checks the validity of the $J_1 - k$ over identifying moment restrictions. In the baseline model, GMM(-2), the null hypothesis of the validity of the $J_1 - k$ over identifying restrictions is not rejected. The 'incremental' Sargan test compares the Sargan statistics for a baseline model with the results for the same model that uses $J_2 - k$ moment restrictions, where $J_2 > J_1$.

[22] Because we have available a relatively large data set, we adopted a significance level of 0.01.

Table 5A Results of using different instrumental variables; innovation panel (N = 1451)

	Estimate	SEE
A) GMM(-2)		
ICT capital	-0.008	0.012
Other capital	0.189	0.123
Labour	0.467	0.069
ICT spillover capital	0.125	0.047
B) GMM(-1)		
ICT capital	0.005	0.010
Other capital	0.198	0.102
Labour	0.329	0.056
ICT spillover capital	0.100	0.043
Incremental Sargan (B – A)	29.2	
Degrees of freedom	12	
Chi2 (0.01)	26.2	
C) SYS-GMM(-2,-2)		
ICT capital	0.017	0.011
Other capital	0.182	0.085
Labour	0.542	0.068
ICT spillover capital	0.139	0.050
Impact ICT initial ICT-intensity on productivity	0.050	0.073
Impact innovation on productivity	0.286	0.065
Incremental Sargan (C – A)	14.9	
Degrees of freedom	6	
Chi2 (0.01)	16.8	
D) SYS-GMM(-2,-1)		
ICT capital	0.025	0.009
Other capital	0.177	0.051
Labour	0.543	0.066
ICT spillover capital	0.131	0.049
Impact ICT initial ICT-intensity on productivity	0.037	0.055
Impact innovation on productivity	0.273	0.048
Incremental Sargan (D – C)	5.1	
Degrees of freedom	3	
Chi2 (0.01)	11.3	

The next step is to compare the results of the GMM- and the SYS-GMM estimator. This is achieved by extending the GMM(-2) model towards a model (SYS-GMM(-2,-2)) that also accounts for the cross-sectional differences in levels, thereby using a comparable instrumental variable setting as in the baseline model GMM(-2).[23] The results of this exercise are given in entry (C) of Table 5A. Looking at the estimates, it can be verified that also using the cross-sectional differences in levels (in addition to the cross-sectional differences in growth rates), yields more plausible estimates for the parameters of interest. Furthermore, the use of additional moment restrictions cannot be rejected at the chosen significance level for the ‘incremental Sargan’ test.

The last entry of Table 5A builds on model (C) by extending the set of instrumental variables to include ΔX_{t-1} in addition to ΔX_{t-2} as instrumental variables. This extension yields the reference model as presented in the main text of the paper. For this variant (labelled model (D)) we arrive at the conclusion that including ΔX_{t-1} in addition to ΔX_{t-2} and earlier growth rates makes sense as the precision of all estimates improves considerably due to the use of the additional instrumental variables concerned. Furthermore, the ‘incremental Sargan’ test statistics validates the use of ΔX_{t-1} as additional instrumental variables.

To sum up, applying the SYS-GMM method seems to pays off in terms of more precise estimates for the parameters of interest. This can be understood as consecutive growth rates show much lower correlations than consecutive level variables in the standard GMM method.[24]

[23]The similarity of SYS-GMM (-2,-2) and GMM(-2) estimates refers to the inclusion of ΔX_{t-2} and earlier growth rates in the SYS-GMM method.

[24] We recall that in our implementation we only use the level-equation for 1998. This allows us to use different (lagged) growth rates as instrumental variables.

Chapter 6

ICT and productivity*

Abstract

This chapter investigates the relative importance of different channels through which information and communication technology (ICT) may have boosted labour productivity growth for the Netherlands at different levels of aggregation. Using Dutch firm-level data for the period 1994-1998, it shows that ICT and other types of innovation have the potential to remain important sources of productivity growth, especially if we account for ICT spillovers and the interaction between ICT and innovation. Indeed, the rebound of Total Factor Productivity in the second half of the previous decade seems to be related to the boom of investment in ICT.

6.1 Introduction

One of the most impressive stylised facts of the previous decade was the economy-wide acceleration of ICT investment. At the end of the 1990s, when economic growth was at its height, many people, including some economists (see, e.g., Kelly, 1997), believed that ICT had drastically changed the economy. ICT had altered the way in which markets operate. Economic growth and productivity growth would be permanently high, the business cycle would be gone forever, and ICT would simply banish inflation. They baptised it as the New Economy, with ICT as the backbone.

Indeed, some evidence was there, but not all signs were convincing. US economic growth accelerated in the second half of the 1990s. Its inflation remained modest, even at low rates of unemployment. The explanation was mostly an ICT story. Due to rapid technology improvements in production, the US ICT-producing manufacturing sector experienced huge productivity gains in the course of the last decade. However, there was little, if any, evidence on productivity of significant spillover effects from the use of ICT to the entire economy.

Once we set foot into the 21st century, it seemed that enthusiasm for ICT suddenly started to wane. The sales of ICT products began to falter, due to the saturation of PC markets and disappearance of the Y2K bonus, among other reasons. The business cycle was still alive. Economic growth started to dwindle all over the world. Main economic regions ended up in a cyclical downturn and inflation picked up. Even in the US, the long period of exceptional expansion (temporarily) came to an abrupt halt. In the period 2001-2002, growth rates of US GDP were much lower than experienced in the second half of the 1990s.

Although enthusiasm for ICT has reduced, one of the big puzzles about ICT still is to explain why firms and countries differ so widely in their ability to make productive use of the potentials entailed in these new technologies. While there exists broad evidence that the diffusion of ICT

* This chapter, co-authored by Henry van der Wiel, appeared as Chapter 6 of 'Fostering Productivity: Patterns, Determinants and Policy Implications', Contributions to Economic Analysis, no. 263, 2004, Elsevier Publishers, Amsterdam.

has led to substantial increases in labour productivity throughout the US economy, results for European countries are rather mixed (Colecchia and Schreyer, 2001; Van Ark, 2001; Van der Wiel, 2001). Similarly, the adoption of ICT and its applications vary largely between firms within the same industry (see, e.g., Bertschek and Fryges, 2002; Van Leeuwen and Van der Wiel, 2003a).

This chapter focuses on the importance of ICT for the Netherlands at different levels of aggregation. The main question to be addressed is whether the predicted benefits of ICT have occurred after all for the Netherlands. Looking backwards to the 1980s and 1990s, productivity growth in the Netherlands seems to be on the way down in an historical and international perspective. Although Dutch productivity level was almost on par with that of the US in the mid 1990s, Dutch productivity growth performance could not match the considerable US productivity gains since then (McGuckin et al., 2001).

Using the growth accounting framework, we first analyse through which channels ICT might have affected Dutch productivity growth at the industry level. Next, to gain deeper insights into the relationship between ICT and productivity, we move beyond the aggregated figures and look at lower levels of aggregation. We, therefore, make use of extensive panels of firm-level data consisting of firms belonging to the Dutch services sector; the productivity performance of parts of the Dutch market services has been disappointing in an international and historical perspective (Van der Wiel, 2001). Moreover, those micro data enable us to analyse two related topics: innovational complementarities and the existence of spillover effects.

The chapter is organised as follows. In the following part, we set out the theoretical background, empirical models and describe the data sources for both the aggregated and firm-level data. In Section 6.3 we present the empirical evidence of the role of ICT and innovation for productivity for the Netherlands as a whole and for the main industries. Section 6.4 discusses the results for the firm-level data. Section 6.5 compares the results of both aggregation levels. Section 6.6 concludes with some final remarks.

6.2 ICT and productivity: theoretical background, empirical models and data

6.2.1 Theoretical background

Based on its various uses, ICT has been compared to other great innovations in the past such as the invention of the steam engine or electricity. These inventions are designated as *general purpose technologies* (GPT) since they are suited to be adopted by a wide range of industries and thereby to unfold a sustained impact on the economy. Moreover, GPT entail a varied potential for technological improvements and a broad scope for innovation complementarities in the ICT producing industries. The innovation of the microprocessor, on which ICT is crucially based, has initiated a series of further innovations such as the development of mainframes, personal computers and electronic networks. This development led to continued productivity gains within the ICT producing industries. Moreover, and maybe most importantly, ICT has also opened a variety of innovation potentials in a variety of sectors outside the ICT producing industries. For example, the use of ICT enables firms to restructure their organisational structures (such as flattening hierarchies and delegation of responsibilities), to re-engineer business processes (such as introducing just-in-time management or engaging in e-commerce) and to develop completely new products (e.g. software and consultancies).

As a GPT, ICT can therefore have wide-ranging productivity effects. ICT can increase labour productivity growth through three well-known mechanisms. First, the rapid increase of technological progress in the ICT-producing industries can make a large contribution to growth if these industries expand much more rapidly than other sectors – even if the ICT sector is relatively small (see OECD, 2001). Second, ICT can stimulate labour productivity through the use of ICT in the production process. Product and process innovations and lower prices for ICT goods and services make the use of ICT as a production factor more attractive. This leads to higher capital intensity per working person (also known as capital deepening), which in turn stimulates labour productivity. There is also a third route, but this route has been heavily debated. Through technology spillovers and network effects, the use of ICT can lead to higher Total Factor Productivity (TFP) growth as well.[1] ICT spillovers emerge when social returns on investment exceed their private returns – a case that seems to be rather relevant for investment in ICT because the benefits of computer usage increase when more users adopt ICT. New ICT applications in combination with organisational changes could ensure greater business efficiency and reduce X-inefficiency. Through good co-ordination, savings could be made on transaction costs in all the links in the production chain. ICT can also contribute to the innovative ability of businesses. Furthermore, network externalities enhance the benefits of the investor in a particular technology as the number of users of compatible products or technologies expands (standardisation benefit).

The 'ICT boom' has given rise to many discussions about the potential of ICT to yield production *externalities* and the role of ICT in the resurgence of productivity in the US in the second half of the previous decade (see, e.g., Jorgenson and Stiroh, 2000; Gordon, 2000). The debate has been fuelled by, among others, the unclear empirical relation between ICT use and TFP growth.

There are primarily two positions. Either this rebound of TFP growth is due to technological progress in the ICT-producing sector itself or it is (also) caused by efficiency gains or spillover effects in ICT-using sectors. The proponents of the former position emphasise that the ICT revolution is a pure neoclassical story of relative price declines and input substitution. More ICT

[1] TFP growth arises if the output increases without additional inputs.

capital per worker enhances labour productivity in the ICT-using industries but not their TFP growth. Proponents of the other position assume that ICT differs from other inputs because of network externalities and spillovers. Those characteristics induce TFP growth. Although the views still differ slightly, a consensus among economists has emerged that both the production and use of ICT have contributed considerably to the resurgence of US productivity in the second half of the 1990s.

In addition to externalities, another feature of ICT is its relationship with *innovation*. Several studies have argued that the use of ICT requires a variety of complementary innovation efforts in order to reap the potentials of productivity gains entailed by it (Bresnahan and Greenstein, 1996; Bresnahan et al., 2002; Hempell, 2002). Although a variety of anecdotal evidence exists and case studies point to the crucial role of innovations for a successful implementation of ICT (Brynjolfsson and Hitt, 2000), empirical studies of the topic are scarce. ICT adoption is generally most advanced in the service sector (OECD 2000a). Moreover, business-related services have been the most important driver of economic growth in industrialised countries (OECD, 2000b). Despite this key role of services, most of the empirical literature analysing the productivity impacts of ICT at the firm level has concentrated on manufacturing. Although developments in manufacturing are not totally disregarded, we explicitly focus the empirical analysis of this chapter on market services.

6.2.2 Empirical models

The main question analysed in this chapter is whether ICT did affect labour productivity growth in the Netherlands. As it is still subject to debate, we also investigate the relative importance of different channels through which ICT can boost labour productivity growth. In that respect, the role of complementary innovations and spillovers will be examined. Regarding the former, the hypothesis is that firms that launch new products, adopt new processes or adjust their organisational structure can reap higher benefits from ICT investment than firms that refrain from such complementary efforts. This implies that the marginal product of ICT is higher in innovative firms as compared to the rest of businesses. The existence of ICT spillovers should at least show up in higher TFP growth.

In order to test these hypotheses empirically, we start with a production function framework with two types of capital, i.e. ICT capital and non-ICT capital (henceforth entitled as other capital):

$$Y_{it} = AL_{it}^{\beta_1} K_{it}^{\beta_2} ICT_{it}^{\beta_3} e^{\eta_i + \varepsilon_{it}} \qquad (1)$$

with Y_{it} denoting value added of firm (or industry) i in period t, L_{it} labour input, ICT_{it} the amount of ICT capital and K_{it} represents other capital. η_i captures unobserved determinants of the productivity of firm/industry i and ε_{it} represents independently and normally distributed shocks. To analyse growth rates, we transform equation (1) into a linear model by taking logarithms. Simple rearranging then yields the basic empirical model:

$$y_{it} = \alpha + \beta_1 l_{it} + \beta_2 k_{it} + \beta_3 ict + \eta_i + \varepsilon_{it} \tag{2}$$

where small letters denote the corresponding logarithms.

The elasticities needed to measure the impact of ICT and other sources on labour productivity growth are not directly available and thus have to be estimated in some way. This paper uses two methods:

- growth accounting method
- econometric approach.

In essence, these both methods are related because they are based on the same theoretical framework as described in equation (2).

The growth accounting method solves the problem of unknown elasticities by assuming that these can be set equal to the observable input shares. In the econometric type of work, the elasticities are obtained after applying some econometric method. Due to data availability, we apply the growth accounting method at the aggregated level (Section 6.3) and the econometric approach at the firm level (Section6.4).

With detailed Dutch firm-level data at hand, we are also able to take into account the effect of spillovers and innovation complementarities. In that case, equation (2) is augmented with additional variables.[2] We estimated the production function simultaneously in levels, and first differences by using SYS-GMM (see the Appendix 6.1). This econometric method also accounts for firm-specific unobservable effects as well as for measurement errors and causality biases.

6.2.3 Data

This research uses two main sources: CPB's sectoral growth accounting database and firm-level data of Statistics Netherlands. CPB's database includes data on Dutch industries supplied by and collected by Statistics Netherlands, and in particular data from the National Accounts. It covers the period 1948 up to the present.[3] The latter source is an extensive set of firm-level data consisting of firms belonging to the Dutch service and manufacturing sector. This data set covers the period 1994-1998 and is constructed after linking the detailed accounting data collected in the yearly Production Surveys of Statistics Netherlands.

Data on capital inputs were not directly available in the second sources. We therefore constructed stocks of ICT and other capital by using the Perpetual Inventory Method and investment data. For the empirical analysis of the impact of innovation, firm-level data from the

---

[2] More details on the empirical models and on data can be found in the appendix.
[3] More on this growth-accounting database can be found in Van der Wiel (2001).

Community Innovation Survey (CIS) are employed. These data can be linked to the accounting firm-level data.

Similar to the well-known practice followed for the modelling of R&D spillovers (see, e.g., Jacobs et al., 2002), we construct ICT spillover capital stocks at the industry level and use these (proximate) spillover indicators to capture the impact of production externalities. This has been achieved by subtracting a firm's own ICT capital stock from the industry aggregate. Thus, (untransformed) approximate ICT spillover capital for firm i belonging to service industry S is obtained as:[4]

$$SICT_{it} = \sum_{j=1, j \neq i}^{N(S)} ICT_{jt} .$$

The model implicitly assumes that ICT spillovers are of a technical nature, affecting the location and structure of the production frontier. It goes without saying that this measure cannot be more than an approximation of the ICT adoption outside of the individual firm. As measuring ICT spillovers at the firm level is still in its infancy, our indicator is a first attempt to quantify spillovers of this type. The appropriateness of the adopted spillover indicator depends on the relative importance of intra-industry linkages. The market service sector consists of many trade firms. Therefore, taking also into account the importance of business-to-business communications for trade firms, the assumptions underlying the construction of our approximate ICT spillover indicator seem not to be at odds. Moreover, and contrary to industry-level data, it is impossible to account properly for inter-industry links at the level of the firm. In defence of the argument that data on inter-industry dependencies are more suitable for the analysis of ICT spillovers, one could argue that ICT spillovers predominantly materialise on the firm level. Thus firm-level data may not be such a bad starting point for assessing their importance.

6.3 Empirical evidence on aggregated levels

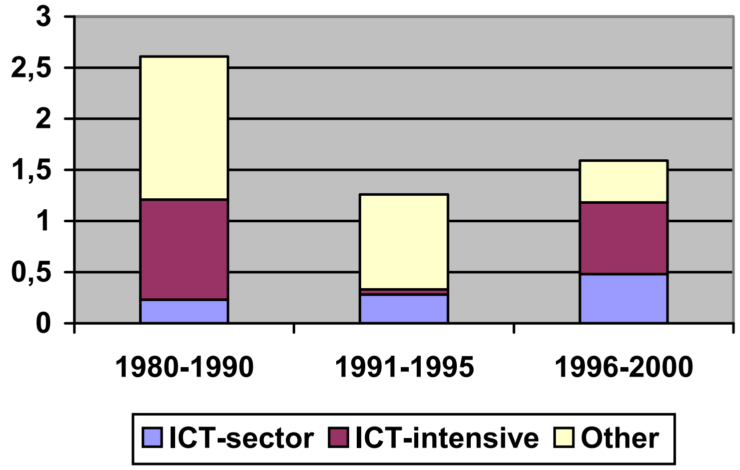
To analyse whether beneficial effects of ICT have already occurred within the Dutch economy on an aggregated level, this chapter divides the market sector into three sectors: ICT sector, ICT-intensive industries and other industries.[5] After a period of structural slowdown,

[4] S is defined as the row in the regularly published Input/Output-table of Statistics Netherlands.

[5] The ICT sector includes electronic equipment, telecom and computer services. ICT-intensive industries includes banking, finance and insurance, business services (except computer services), wholesale and retail trade, paper (products), printing and publishing industry, and metal industry (except electronic equipment). Other industries consist of agriculture, food, textile, wood, chemicals, oil, distribution of electricity, water and gas, construction and transport.

labour productivity growth for the market sector recovered slightly at the end of the 1990s (see Figure 6.1).[6] The acceleration seems to be related to the production and use of ICT. Despite its small size in the Dutch economy, the productivity performance of the ICT sector accounted for a substantial share in the rebound of labour productivity growth of the Dutch market sector. Strong productivity growth in the ICT sector is partly due to increased efficiency in the production of ICT products, particularly ICT-producing services.

Figure 6.1 Contribution of industries to labour productivity growth of Dutch market sector (in %-points), 1980–2000.



Users of ICT, represented by ICT-intensive industries, also seem to benefit from the opportunities it presents and contributed substantially to the productivity acceleration in the market sector. Labour productivity growth rates accelerated markedly in ICT-intensive industries in the late 1990s. Using the growth accounting method, it can be seen that this acceleration in labour productivity growth in the ICT sector and ICT intensive industries can not be attributed to an increase of ICT capital deepening (see Table 6.1). It was faster TFP growth that accompanied the increase. The higher TFP growth in ICT-intensive industries could be related to ICT, but may also stem from developments in the economy that are independent of ICT. This issue will be addressed in the next section. Finally, it can be seen that the other industries in the Netherlands documented a slowdown of productivity growth in the second half of the 1990s.

[6] Notice that productivity growth was absent in the period 2001–2002.

Table 6.1 Decomposition of Dutch labour productivity growth, 1991–2000

	Market sector		ICT sector		ICT-intensive industries		Other industries	
	1991-1995	1996-2000	1991-1995	1996-2000	1991-1995	1996-2000	1991-1995	1996-2000
Annualised growth rates in %								
Labour productivity	1.3	1.6	3.9	4.7	0.2	1.4	2.7	1.0
Contribution of:								
1) ICT capital	0.3	0.4	2.1	1.0	0.3	0.3	0.1	0.2
2) Other capital	0.4	0.0	0.4	–0.2	0.5	0.2	0.6	0.1
3) TFP	0.5	1.2	1.4	3.9	-0.6	1.0	1.9	0.7

Source: Van der Wiel (2001)

6.3.1 An international comparison

Towards the end of the 1990s, it became clear that the macroeconomic productivity performance of the US was remarkably better than that of other regions in the world, such as Europe. In fact, labour productivity growth accelerated in the US, whereas Europe's labour productivity growth remained on a track of slower growth. In a European perspective, the Dutch productivity growth slowdown is not at odds and seems to reflect a commonly downward trend. Nevertheless, during the 1990s, the annual growth of productivity in the Netherlands is on average much lower than that of the EU as a whole.[7]

To some extent, the productivity growth difference between the US and Europe, and in particular the Netherlands, comes from the lower direct contribution of ICT-capital services in the EU (see Table 6.2). This is due to lower investments in ICT.

Table 6.2 Decomposition of labour productivity growth for the market sector: an international perspective, 1991–2000

	US		Euro area		Netherlands	
	1991-1995	1996-2000	1991-1995	1996-1999	1991-1995	1996-2000
Annualised growth rates in %						
Labour productivity	1.5	2.6	2.4	1.3	1.3	1.6
Contribution of:						
1) ICT capital	0.6	1.1	0.3	0.4	0.3	0.4
2) Other capital	0.1	0.1	0.8	0.3	0.4	0.0
3) TFP	0.9	1.5	1.4	0.6	0.5	1.2

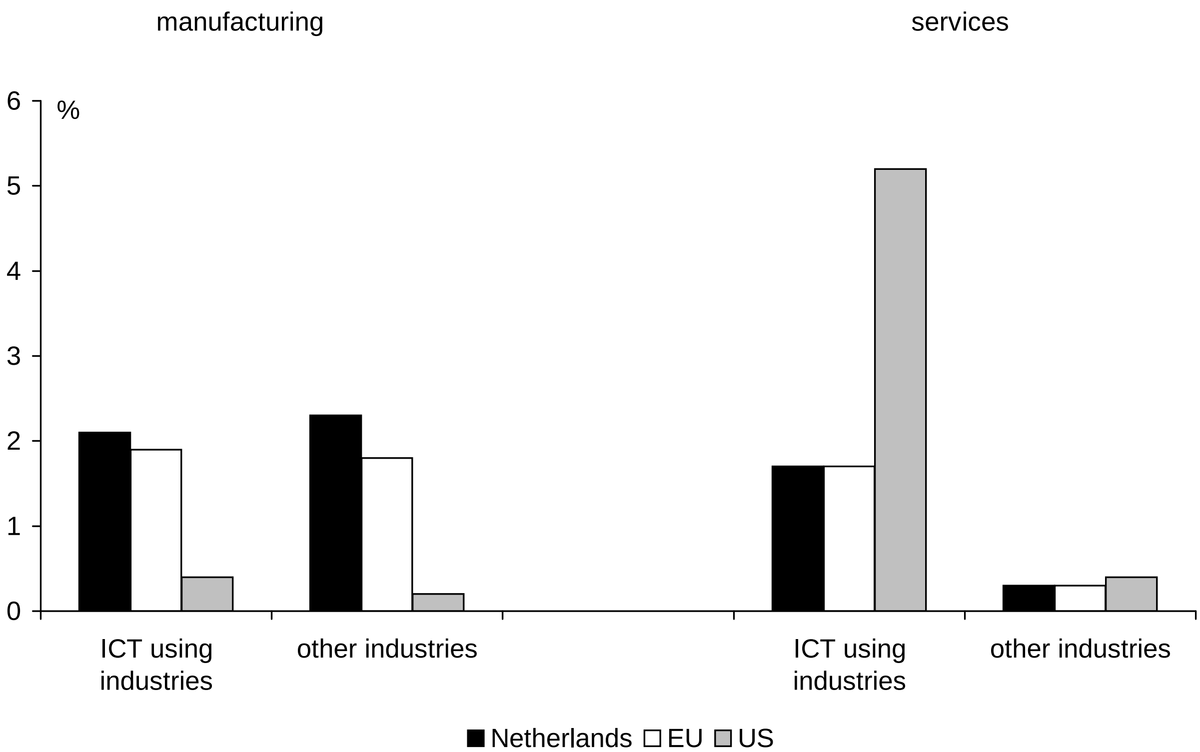
Source: US: Stiroh (2002); Euro area: ECB (2002); Netherlands: Van der Wiel (2001)

[7] This is certainly the case if it concerns figures for the whole economy.

However, the gap in TFP growth rates in the second half of the 1990s seems to drive the difference in the labour productivity performance between the US and Europe. TFP growth seems to be very sluggish in Europe in contrast to the US where TFP accelerated due to a stronger contribution by the ICT-producing industries and ICT-using industries. As the ICT-producing industries are relatively small in both regions, differences in their productivity performance cannot be the main explanation for the gap in TFP growth at an aggregated level. Figure 6.2 provides evidence that the major difference is caused by the ICT-using services. Besides the divergence in the ICT-producing industries, the better productivity performance of the US in the second half of the 1990s stems completely from ICT-using services as in other industries, either ICT-using manufacturing industries or non-ICT using industries, the US performance is worse.

In that respect, for the Netherlands, it is very informative to look at ICT-using services at lower levels of aggregation in more detail; this will be done in the next section. It seems to be that most of the Dutch manufacturing industries perform well in an international perspective.

Figure 6.2 Labour productivity growth performance of selected sectors; an international comparison, 1995–-2001



Source: National Institute of Economic and Social Research (NIESR) and Groningen Growth and Development Centre (GGDC)

6.4 Empirical evidence at the firm level for market services[8]

This section focuses on the relationship between ICT and productivity at the firm level using extensive panels of firm-level data consisting of firms belonging to the Dutch market services sector. The availability of micro-data provides the opportunity of gaining deeper insights of this relationship. One of the main findings of this type of research has been the large differential in the levels and the rates of growth of productivity across firms within the same industry (see e.g. Foster et al., 2001). There is, however, no single explanation for this differential but a whole range of reasons.

For both panels, Table 6.3 presents some descriptive measures for the key variables used in this section. The table clearly confirms the impressive ICT boom in the course of the previous decade. For the complete panel, we obtain an annualised growth of ICT of approximately 20%. This outcome corresponds with growth figures derived from industry level data for the Netherlands (Van der Wiel, 2001).

Table 6.3 Growth rates of productivity and inputs into production for two panels; market services [a]

	ICT intensive	ICT extensive	All
Complete panel			
Number of firms	3847	3981	7828
Labour productivity	1.4	1.6	1.5
ICT capital	4.0	35.2	19.8
Other capital	4.4	4.2	4.3
Labour	1.9	4.0	3.0
Innovation panel			
Number of firms	645	806	1451
Labour productivity	2.4	2.5	2.5
ICT capital	8.8	45.7	29.3
Other capital	3.8	4.2	4.0
Labour	2.0	4.3	3.3

[a] Annualised growth 1994 - 1998.

Firms that were relatively ICT extensive at the beginning of the period show the highest growth rates.[9] Nonetheless, the ICT extensive firms (on average) had a lower level of ICT intensity at the end of the period than was observed at the beginning of the period for their ICT-intensive counterparts. This result suggests that many firms still have potential to improve their productivity by catching up their ICT endeavour.

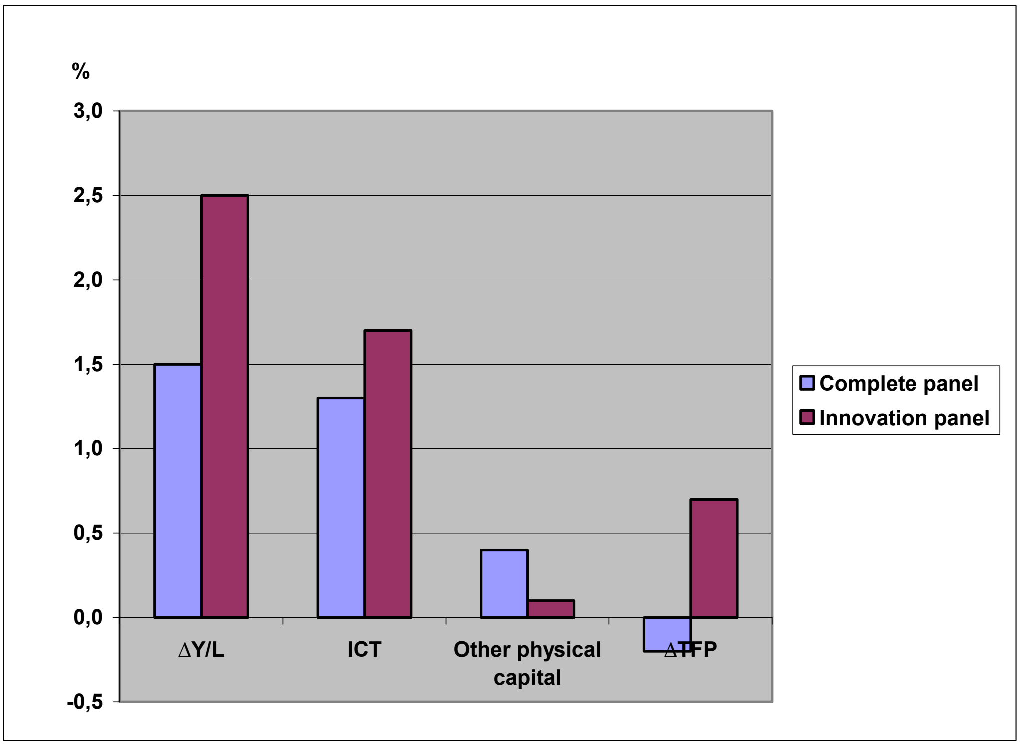
[8] Here, we mainly present the results for market services in graphical form, econometric details and the results for manufacturing can be found in Van Leeuwen and Van der Wiel (2003a).

[9] Firms are labeled ICT intensive if their share of ICT capital in total capital inputs in 1994 was above the median score calculated for the corresponding sector (3-digit NACE).

6.4.1 ICT, innovation and productivity[10]

The descriptive results seem to indicate that innovators had a relatively better productivity performance than the average of firms in the complete panel (respectively 2.5% and 1.5% on an annual basis). The hypothesis is that this outcome is related to relatively high ICT use. This hypothesis was tested by analysing the contribution of ICT and innovation to labour productivity (growth) in a production function framework. Here we use a graphical presentation of this analysis. We will discuss the following: 1) results regarding the direct contribution of ICT to productivity growth, 2) results regarding the contribution of innovation to TFP, and 3) the relation between TFP, innovation and initial ICT intensities.

Figure 6.3 Decomposition of labour productivity growth (=ΔY/L) at the firm level for market services, 1994–1998



We begin by looking at the decomposition of labour productivity growth. Figure 6.3 summarises the results for both panels. The most striking result is that almost all productivity growth in Dutch market services came from ICT capital deepening (labelled ICT). This is due to the high ICT elasticity in combination with high growth rates of ICT capital per worker. The estimate for the ICT elasticity is close to 0.08, a comparable magnitude as those reported by Brynjolffson and Hitt (1995) and Hempell et al. (2002). Moreover, the estimate is about twice as high as the corresponding ICT cost share. Another notable outcome is that TFP growth was

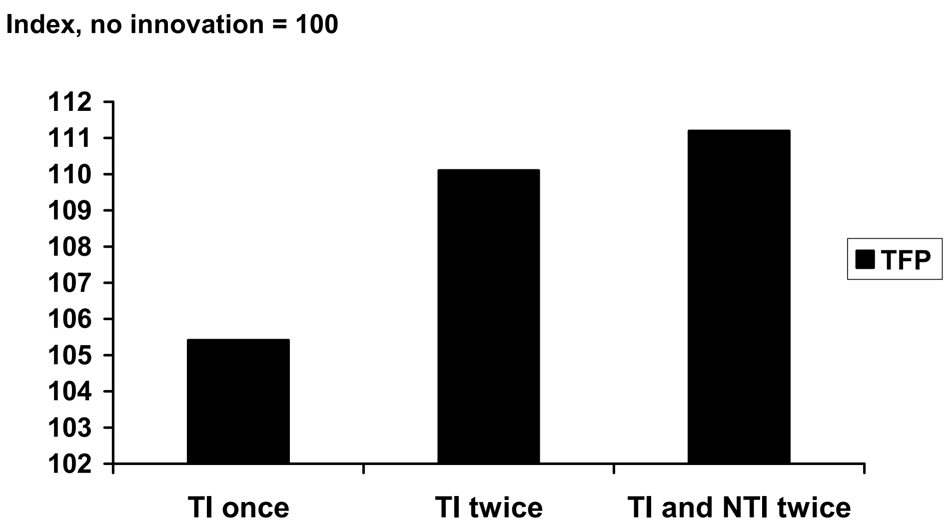
[10] Here, we look at whether ICT induces more innovation. However, it can be questioned that the reversed causality is at stake: innovation stimulates or demands more ICT. SYS-GMM tries to correct for this causality problem.

negative for the complete panel.

Despite similarities with other studies, we will argue that the estimated coefficients of ICT capital for the Netherlands are likely to be biased upward. A possible reason is that no account has been taken of ICT spillovers. The next section will address this issue. As innovation may also be related to ICT use, the neglect of differences in innovativeness may be another reason for suspecting biases of the direct contribution of ICT to productivity (growth). Indeed, using the innovation panel, TFP growth turns out to be positive, and ICT capital deepening a less important source of labour productivity growth. The firms belonging to the innovation panel clearly showed higher growth rates of labour productivity and TFP growth in 1994–1998 than their counterparts.

Being innovative is an important potential source of TFP differentials. Figure 6.4 presents further evidence on this. The figure compares the (average) productivity levels of firms that were innovative or not. Non-innovating firms are the reference group in this comparison. We compare their estimated TFP level in 1998 with the corresponding figures for three types of innovating firms. First, we compare the reference group with the firms that applied technological innovations once (i.e. either in 1994–1996 or in 1996–1998). These firms are labelled 'TI once'. Subsequently, we estimated (average) TFP for the firms that applied technological innovations in both periods (labelled 'TI twice').

Figure 6.4 Relation between innovation and TFP, 1994–1998

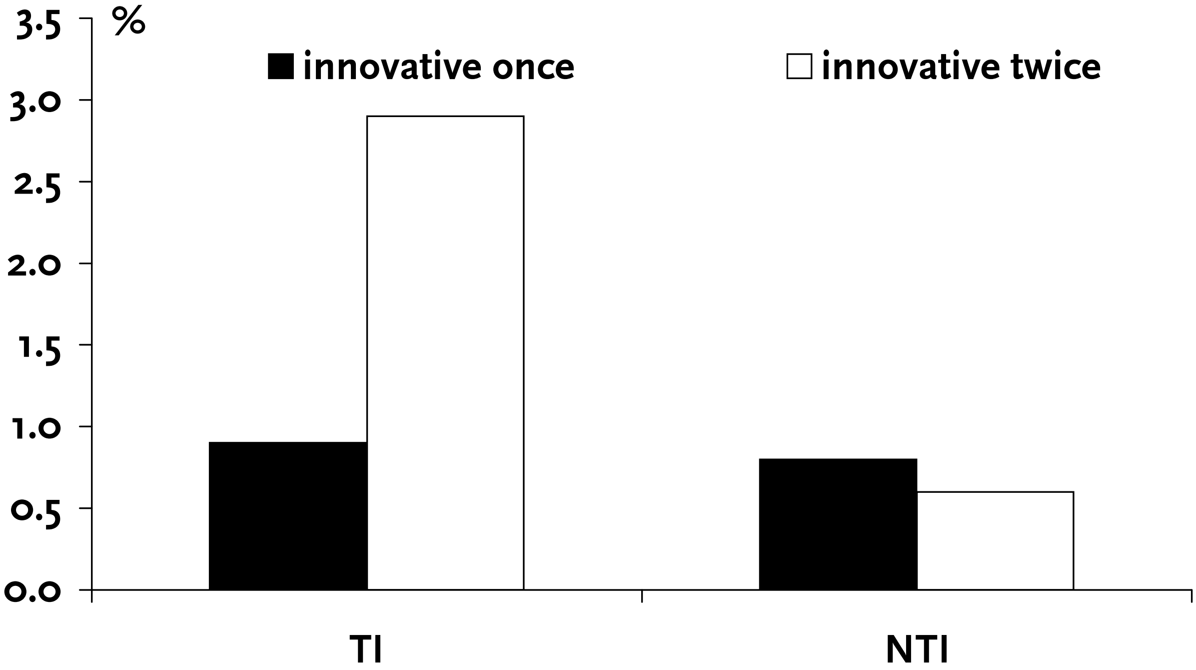


Note: TI once are firms that applied technological innovations either in 1994–1996 or in 1996–1998; TI twice are firms that applied technological innovations in both periods; TI and NTI twice are firms that implemented technological as well as non-technological innovations in both periods.

Finally, we compared the TFP levels of the latter group with the corresponding figures for the firms that implemented technological as well as non-technological innovations (labelled 'TI and NTI twice').

The results summarised in Figure 6.4 suggest that innovation seems to pay off, especially when firms are involved more ‘permanently’ in technological innovation. It can be verified that the TFP difference in 1998 for the firms that implemented innovations in all years was (on average) almost twice as high as the outcome for firms that were only innovative in 1994–1996 or 1996-–1998. Figure 6.3 also indicates that the combination of technological and non-technological innovation ca–n raise TFP further, thereby yielding increasing returns of innovation to TFP. However, this result should be interpreted with care, as we do not have available a very long history of innovativeness for each firm.

Figure 6.5 TFP-growth differences between ICT-intensive and ICT-extensive services firms, 1994–1998



Note: TI is technological innovation; NTI is non-technological innovation.

Finally, we also analysed the link between ICT and innovation in relation to productivity growth by comparing ICT-intensive and ICT-extensive firms (see Figure 6.5). We assume that firms must reach a certain level of ICT adoption in order to be able to capture the fruits of their innovation efforts. Taken on the whole, Figure 6.5 seems to confirm this assertion. The figure presents the (average) TFP growth differential (in percentage points) in the period 1994-1998 of ICT-intensive firms compared to their ICT-extensive counterparts. For all types of innovation, we observe a positive impact of being relatively more ICT intensive at the beginning. In terms of technological innovation, the figure also underlines the importance of being innovative more permanently. Summing up and cutting through the various pieces of empirical evidence: our results indicate that ICT may enhance innovation and that the incremental impact on productivity arising from the positive link between innovation and ICT is more substantial if firms have reached a more substantial level of ICT adoption.

6.4.2 ICT and productivity: do spillovers matter?

According to the industry-level results based on the growth accounting method, the increased use of ICT was accompanied by an acceleration of the TFP component of Dutch labour productivity growth. In contrast, so far, the evidence based on firm-level data underline the importance of ICT capital deepening. Therefore, which part of labour productivity growth is channelled through TFP growth and which part is due to capital deepening remains open to debate.

Here, we explicitly explore the existence of ICT spillovers for the Netherlands at the firm level. By including an ICT spillover indicator, the production function is augmented to test this hypothesis. As far as we know, this is a novelty at this level of aggregation.[11]

Figure 6.6 Contribution to labour productivity growth of ICT capital deepening (CD): Dutch market services 1994–998

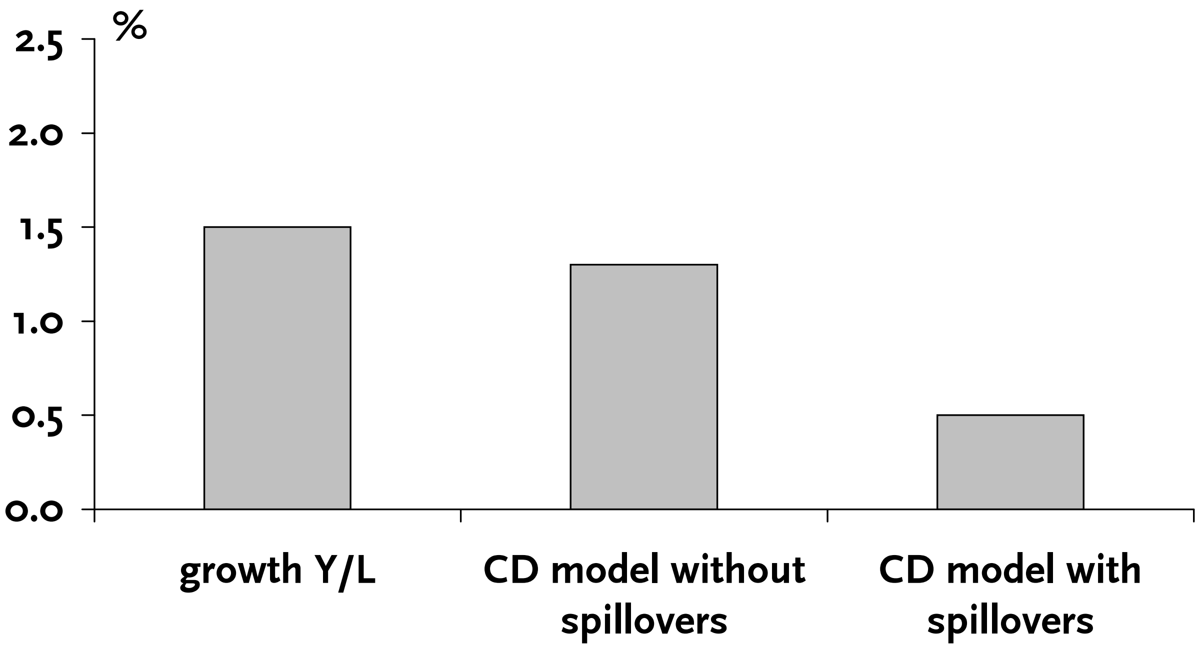


Figure 6.6 compares the contribution of ICT capital deepening (labelled 'CD') to labour productivity growth for the model with or without spillovers. As discussed above, the relatively high estimate for the ICT elasticity suggests excess rates of returns and raises some doubt about whether this result is biased due to the omission of complementary costs and spillover effects. The available data only allow addressing the latter issue. Indeed, Figure 6.6 clearly illustrates that if ICT spillovers are taken into account more explicitly, the contribution of ICT capital deepening is lowered substantially.[12] It becomes more comparable to the results found on the

[11] As discussed, measuring ICT spillovers at the firm level is still in its infancy. Our indicator is in that respect only a first approximation. Further research is definitely needed whether it is possible to improve this indicator at the firm level.

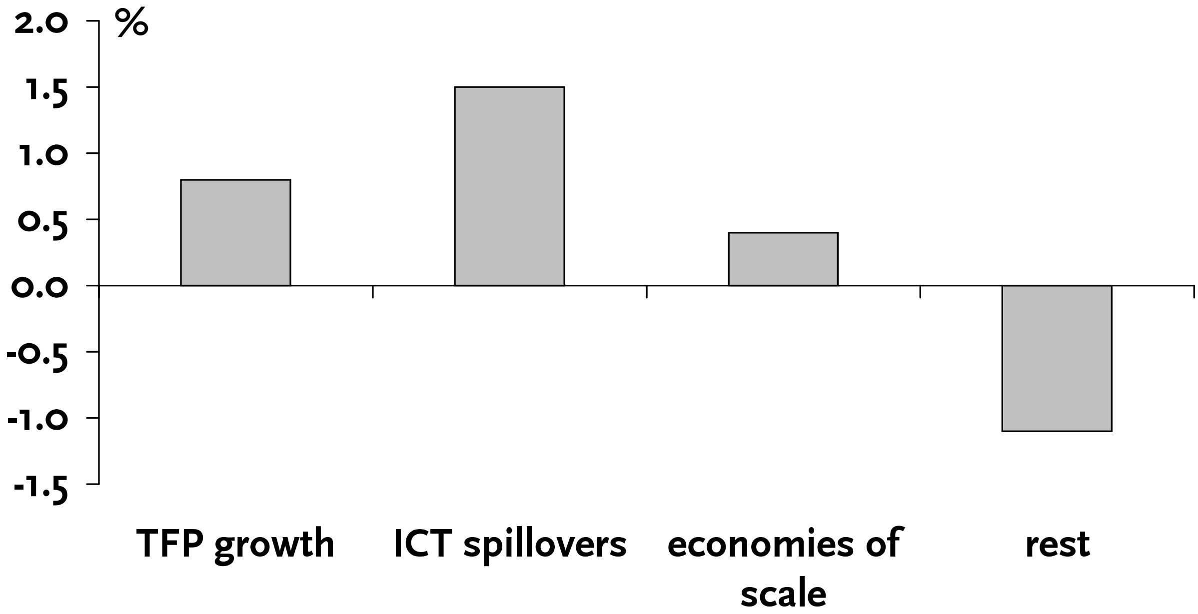
[12] For the sake of completeness, the coefficient of the ICT spillover is statistically significant.

industry and macro level: on average, about one-third of labour productivity growth can be attributed to own-ICT-capital deepening.

Based on the model with spillovers, Figure 6.7 presents the results of the breakdown of TFP growth in ICT spillover, economies of scale and a rest component of unspecified sources for the Dutch market services. The contribution of ICT spillovers to TFP growth is approximately 1.5%. This result seems to be extraordinary high as it leads to a negative rest component. On the other hand, this high contribution is fairly consistent with the outcome of the Mun and Nadiri (2002) study, which analysed the importance of ICT rent spillovers at the industry level with the help of inter-industry commodity flows. Their study found an elasticity of total costs with respect to ICT spillovers that varied between 2% and 3% for market services.

In spite of this, two caveats are worth mentioning when interpreting the decomposition of TFP growth of Figure 6.7. First, the contribution of ICT spillovers to TFP growth is calculated as the mean of firm-level spillover effects. As many firms in our sample are relatively small (but have the same weight as the largest firms), this may explain part of the unexpected high average contribution of ICT spillovers to TFP growth reported here. Second, our measure of ICT spillover capital may be too crude as it overemphasises the importance of intra-industry linkages and ignores other economic linkages. If the latter linkages were equally important, then this would imply that ICT spillover capital was underestimated and that the (estimated) contribution of ICT spillovers to TFP growth could be overestimated.

Figure 6.7 Decomposition of Total Factor Productivity (TFP) growth: Dutch market services, 1994–1998



Therefore, although our results show that ICT spillovers do matter as a source of TFP growth, further research is needed to investigate the sensitivity of our results with respect to the chosen definition of ICT spillovers and the link between firm-level and aggregate TFP growth.

Finally, the result for the scale parameter shows up in a contribution of 0.4% (about 25% of labour productivity growth) and emphasises the importance of scale economies in market services (see Kox et al., 2003).

6.5 Do firm-level results match with aggregated results?

This section compares the results from the econometric approach with the growth accounting calculations for the Netherlands. In so doing, we attempt to reconcile the different pieces of empirical evidence in the international literature regarding the contribution of ICT to productivity growth and the importance of the different channels.

In spite of the unprecedented growth of ICT capital per employee, the direct contribution of ICT to labour productivity remained rather modest in the previous decade, according to growth accounting studies focussed at the industry or macro level (see, e.g., Stiroh, 2002; Van der Wiel, 2001). With TFP growth accelerating at the same time, this result suggests that the impact of ICT was channelled mainly through TFP. In contrast, using econometric techniques, the evidence based on firm-level data underlines the importance of ICT capital deepening, as in many cases the econometric ICT elasticities turned out to be much higher than seems to be consistent with the (still) relatively low ICT cost shares (see, e.g., Brynjolfsson and Hitt, 2000; Van Leeuwen and Van der Wiel, 2003b).

As discussed in Section 6.2, in essence, these two strands of research are related because they are based on the same theoretical production function framework. Nonetheless, differences occur and could be due to different kind of methods, omission of variables, and/or aggregation problems. The analysis for the Netherlands presented above suggests that the neglect of spillovers in the econometric approach may explain the discrepancy between different levels of aggregation.

Table 6.4 shows that, after controlling for ICT externalities via the ICT spillover indicator employed, the contribution of ICT capital deepening of both methods are very similar. Nevertheless, our econometric results provide additional insights by demonstrating that the contribution of ICT spillovers to Dutch productivity growth in the years of the ICT boom was substantial.

Finally, comparing the outcomes of micro and macro studies is still in its infancy. As Bartelsman and Doms (2000) formulated *"Greater attention should be paid to the aggregate implications of the findings from micro data and to micro-implications of findings at the aggregate level"*.

Table 6.4 Decomposition of labour productivity growth using firm-level data, market services 1994–1998

	Growth accounting	Econometrics
Annualised growth (%)		
Complete panel (N= 7828)	1.5	1.5
Contribution of:		
ICT-capital deepening	0.5	0.5
Other capital deepening	0.3	0.2
TFP growth	0.7	0.8

6.6 Conclusions

The main findings of this chapter may be summarised as follows. Labour productivity growth in the Dutch market sector slightly accelerated in the second half of the 1990s, due to the performance of ICT-producing and ICT-intensive industries. In contrast, labour productivity growth further slowed down in less ICT-intensive industries. Based on the growth accounting method, it can be shown that the increases in the ICT sector and ICT-intensive industries were mainly accompanied by faster TFP growth. Although both sectors experienced positive growth effects of ICT through capital deepening, those effects were small. To what extent the rebound of TFP growth in the second half of the previous decade was related to the boom of investment in ICT remains open to debate in the growth accounting method.

Therefore, by including ICT spillovers explicitly in a production function model and using an extensive panel of firm-level data for Dutch industries, we attempt to assess which part of labour productivity growth is (indirectly) channelled through TFP growth by ICT. Additionally, this study analyses the importance of innovation for productivity and takes into account that innovation and ICT use can be complementary.

The firm-level results point to a sizable direct contribution of ICT to Dutch labour productivity growth. However, this contribution is likely to be biased upwards if leaving out other sources of productivity that are correlated with ICT use. It is shown that the (direct) contribution of ICT capital deepening to labour productivity growth is lower but still significant if ICT spillovers are taken into account.

In so doing, we were also able to reconcile the different pieces of empirical evidence in the literature regarding the contribution of ICT to productivity growth at different levels of aggregation. For the Netherlands, it is shown that, after accounting for ICT spillovers, the results on firm-level data are more in line with those reported in growth accounting studies on higher levels of aggregation. Nevertheless, our econometric results provide deeper insights than the growth accounting studies by demonstrating that the contribution of ICT spillovers to productivity growth in the years of the ICT boom was substantial.

We also found support for the assumption that ICT enhances the innovation performance of firms, thereby contributing to labour productivity growth in a more indirect way. Moreover, it is illustrated that the contribution of ICT capital deepening is raised when firms combine ICT use and technological innovations on a more permanent basis.

Looking forward, taking into account projected slower growth rates of labour supply, Dutch labour productivity growth must increase in the coming years in order to prevent a substantial decline in GDP growth. This study shows that ICT still has the potential to induce higher productivity growth rates in the Netherlands across the economy. In particular, less ICT-intensive industries and firms could improve their productivity if they catch up with developments seen elsewhere.

Here, we have made an attempt to construct and quantify the effect of ICT spillovers at the firm level for the Netherlands and the results seem to be very promising. As far as we know, this is a novelty at this level of aggregation. However, two comments should be considered. First, due to a lack of data availability, the applied spillover indicator is only an approximation. Further research is needed as to whether an extension of the approximation is achievable and to check whether the presented firm-level results are robust on higher levels of aggregation. Second, besides the main topics of this contribution – ICT and innovation – human capital is an important source of labour productivity. Investments in education and training lead to the accumulation of knowledge and skills. Therefore, an increase of human capital positively affects labour productivity growth. As human capital, ICT and innovation are strongly interrelated, neglecting one of these productivity determinants could lead up to an overestimation of the effect of the included determinants in a regression. Unfortunately, Statistics Netherlands hardly collect any measure of human capital at the firm level.

References

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68, 29-51.

Ark, B. van, 2001. The renewal of the old economy: an international comparative perspective, technical report. OECD, Paris.

Bartelsman, E., Doms, M., 2000. Understanding productivity: lessons from longitudinal microdata. Journal of Economic Literature, 38, 569-594

Bertschek, I., Fryges, H., 2002. The adoption of business–to–business e-commerce: empirical evidence for German companies. ZEW Discussion Paper No. 02–05. Centre for European Economic Research.

Blundell, R., Bond, S., 1998, Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87, 115-143.

Bresnahan, T., Greenstein, S., 1996. Technical progress and co-invention in computing and in

the use of computers. Brooking Papers on Economic Activity, Microeconomics pp. 1–77.
Bresnahan, T. F., Brynjolfsson, E., and L.M., 2002. Information technology, workplace organization, and the demand for Skilled labor: firm-level evidence. Quarterly Journal of Economics, 117, 339- 376.
Brynjolfsson, E., Hitt, L., 1995. Information technology as a factor of production: The role of differences among firms, Economics of Innovation and New Technology, 3, 183-199.
Brynjolfsson, E., Hitt, L., 2000. Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives, 14, 23-48.
European Central Bank, 2002. New technologies and productivity growth in the Euro area. Working paper no. 122, by Vijselaar, F., Albers, R., February 2002.
Colecchia, A., Schreyer, P., 2001. ICT investment and economic growth in the 1990s: is the United States a unique case? STI Working Papers 2001/7, OECD, Paris.
Foster, L., Haltiwanger, J., Krizan, C.J., 2001. Aggregate productivity growth: lessons from microeconomic evidence, in: New Developments in Productivity Analysis. NBER/University of Chicago Press.
Gordon, R.J., 2000. Does the 'New Economy' measure up to the great inventions of the past? Journal of Economic Perspectives, 14, 49-77.
Hempell, T., 2002. What's spurious, what's real? Measuring the productivity impact of ICT at the firm-level. ZEW Discussion Paper 02-42. Centre for European Economic Research.
Hempell, T., Leeuwen, G. van, Wiel, H.P. van der, 2002. ICT, innovation and business performance in services: Evidence for Germany and the Netherlands. OECD, DSTI/EAS/IND/SWP/AH(2002)7.
Jacobs, B., Nahuis, R., Tang, P.J.G., 2002. Sectoral productivity growth and R&D spillovers in the Netherlands. De Economist, 159(2), 181-210.
Jorgenson, D.W., Stiroh, K.J., 2000. Raising the speed limit: U.S. economic growth in the information age. Brookings Papers on Economic Activity, pp. 451-476.
Kelly, K., 1997. New rules for the new economy.
Kox, H., Leeuwen, G. van, Wiel, H.P. van der, 2003. Scale economies in business services. CPB Discussion Paper (forthcoming).
Leeuwen, G. van, Wiel, H.P. van der, 2003a. Do ICT spillovers matter? Empirical evidence for The Netherlands. CPB Discussion Paper, 26
Leeuwen, G. van, Wiel, H.P. van der, 2003b. ICT, innovation and productivity. CPB Report 2003/2.
McGuckin, R.H., Ark, B. van, 2001. Performance 2000, The Conference Board.
Mun, S.B., Nadiri, M.I., 2002. Information technology externalities: Empirical evidence from 42 U.S. industries. NBER Working Paper 9272.
OECD, 2000a. A new economy? The changing role of innovation and information technology

in growth. OECD, Paris.
OECD, 2000b. The Service Economy, Business and Industry Policy Forum Series, STI/OECD.
OECD, 2001. The New Economy: Beyond the Hype. Paris.
Stiroh, K.J., 2002. Are ICT spillovers driving the new economy? Review of Income and Wealth, vol. 48, no 1.
Wiel, H.P. van der, 2001. Does ICT boost Dutch productivity growth? CPB Document no. 016.

Appendix 6.1 Estimation methods, econometric models and data

This appendix is structured as follows. We start with a short explanation of the SYS-GMM estimation method and subsequently we provide more details about the enhanced production function model and about the construction of two panel data sets.

SYS-GMM estimation method

In this study we use heterogenous firm-level data to investigate the relation between ICT use, innovation and productivity. It is well-known that the tremendous heterogeneity in performance records at the firm-level can also be attributed to unobservable firm-specific effects. Ignoring these effects may bias OLS estimates severely. The usual approach to circumvent this problem is to eliminate the firm specific parameters by transforming the model into growth rates and then use the GMM method of estimation. Arellano and Bover (1995) and Blundell and Bond (1998) showed that this method may fail in case of weak instruments due to a lack of sufficient correlation between explanatory variables and instruments. To overcome this problem they introduced the method of SYS-GMM. This is a generalised instrumental variables method that uses both the equations in levels and growth rates to account for various sources of estimation biases like measurement errors, reversed causality or endogeneity of explanatory variables. This method has been applied in this study.

The enhanced production function model

To estimate the contribution of ICT and innovation to productivity, we used the following labour productivity equation derived from a Cobb-Douglas specification. In logarithmic form, this specification reads:

$$y_{it} - l_{it} = \beta_1 (ict_{it} - l_{it}) + \beta_2 E_i (ict_{it} - l_{it}) + \beta_3 P_i (ict_{it} - l_{it}) + \beta_4 (k_{it} - l_{it}) + \beta_5 E_i (k_{it} - l_{it})$$

$$+ \beta_6 P_i (k_{it} - l_{it}) + \beta_7 l_{it} + \alpha_i + \gamma_1 E_i + \gamma_2 P_i + \varepsilon_{it}\,, \tag{4}$$

with y value added per employee (in constant prices), ict denote ICT capital stock (in constant prices), k is stock of other capital (in constant prices), l is number of employed persons. The equation uses two dummies to assess the effect of different innovation activities: E = 1 for innovations applied in 1994–1996 or 1996–1998; P = 1 if firms applied innovations in 1994–1996 as well as 1996–1998. Subscripts i and t in equation (4) refer to firms and time respectively, α_i represents the contribution to productivity of unobserved firm-specific variables, and ε_{it} is an independent and identically distributed disturbance term.

Equation (4) enables us to compare the relative importance of capital deepening and TFP, as well as the contribution of innovation to TFP. The coefficients β_1, β_2 and β_3 measure the direct contribution of ICT, including the interaction of innovation on ICT capital deepening. TFP in (4) is represented by $\beta_7 l_{it} + \alpha_i + \gamma_1 I_i + \gamma_2 P_i$. Furthermore, the coefficients γ_1 and γ_2 measure the contribution of innovation to TFP, which can be estimated only for the innovation panel. We re-estimated the model for different definitions of innovativeness, in order to obtain a better understanding of the importance of various types of innovation. Subsequently, we used the model estimates to assess the relative importance for labour productivity of (ICT) capital deepening and the contribution of innovation to TFP. This assessment was carried out for two samples: the firms that were relatively ICT intensive and the firms that were relatively ICT extensive at the beginning of the period.

To disentangle the effect of ICT on labour productivity into a contribution of capital deepening and TFP, we used the following equation derived from a Cobb-Douglas specification. In logarithmic form, this specification reads as follows:

$$y_{it} - l_{it} = \gamma_1(ict_{it} - l_{it}) + \gamma_2(k_{it} - l_{it}) + (1 - \gamma_1 - \gamma_2)l_{it} + \gamma_3 sict_{it} + \gamma_4 I_i + \alpha_i + \varepsilon_{it} \tag{5}$$

where *sict* represents stock of ICT spillover capital (in constant prices), and I is a dummy variable that captures the productivity differences related to initial ICT intensities (ICT-extensive firms are the reference group).

Two panels

For the econometric analysis, we used accounting firm-level data collected in the yearly Production Surveys of Statistics Netherlands. We constructed two (balanced) panels – complete panel and innovation panel – covering the period 1993–1999. The complete panel consists of 7828 market services firms (i.e. wholesale and retail trade, business services) and 2558 manufacturing containing only those firms for which consecutive data on capital inputs were available for at least five years. Linking the complete panel to the two waves of the innovation survey (CIS 2, covering 1994–1996, and CIS 2.5, covering 1996–1998), we created the innovation panel.[13] This panel includes 1091 manufacturing firms and 1451 services firms.

The innovation panel enables us to determine which firms were innovative or not. Moreover, the Dutch CIS makes a distinction between technological and non-technological innovation. Technological innovation is defined as the introduction of new or improved products (product innovation) or means of production (process innovation). Non-technological innovations are changes in strategy, marketing, organisation and management.

[13] Due to selectivity, the innovation panel contains relatively few small- and medium-sized firms. In the regression analysis we control for possible selectivity bias.

Chapter 7

Market structure, productivity and scale in European business services*

Abstract

Labour productivity in business-services industry tends to lag behind the rest of the economy. The present chapter investigates whether or not labour productivity in European business services is affected by unexploited economies of scale. Moreover, it analyses whether the incidence of scale sub-optimality is related to characteristics of the market or to national regulation characteristics. The econometric analysis is based on a production function model in combination with a distance-to-the-frontier model. A main result is that we find evidence for the existence of increasing returns to scale in business services firms. Throughout the EU, firms with less than 20 persons have significantly lower average level of labour productivity than the rest of the business-services industry. We find two explanatory factors for the level of scale inefficiency. The first is the level of policy-caused firm-entry costs; higher start-up costs for new firms go along with more scale inefficiency for business-services firms. Secondly, we find evidence that business-services markets tend to be segmented by firm size: firms tend to compete predominantly with firms in their own size segment of the markets. Scale-related inefficiencies may to some extent be compensated by more competition within a firm's own size segment. If a firm operates in a more "crowded" segment this has a significant and positive impact on its labour productivity. We derive some policy implications from our findings.

7.1 Introduction

During the past 15 years, business-services industry in most OECD countries has been among the industries with the highest growth pace. This held for its production, but even more for its employment growth. Labour productivity in business-services industry tends to lag behind the rest of the economy. This is reason for policy concern, because business-services industry nowadays has become a large part of OECD economies, and it is a major supplier of inputs to other industries. Low productivity in a large economic sector may negatively affect macroeconomic growth in a direct way. One of the findings of a large Dutch research project on the causes of the sluggish productivity growth in business services was that scale sub-optimality may be a source of the poor productivity performance in business services.[1] The then available statistical evidence suggested that the overwhelming majority of firms in this industry operates at a scale where potential scale economies are left unexploited.

The present paper investigates this hypothesis more profoundly by analyzing the scale impacts on productivity in the business services in an internationally comparative context. More specifically, we investigate econometrically the following questions:

- is productivity in European business services affected by unexploited economies of scale? If this is the case,

---

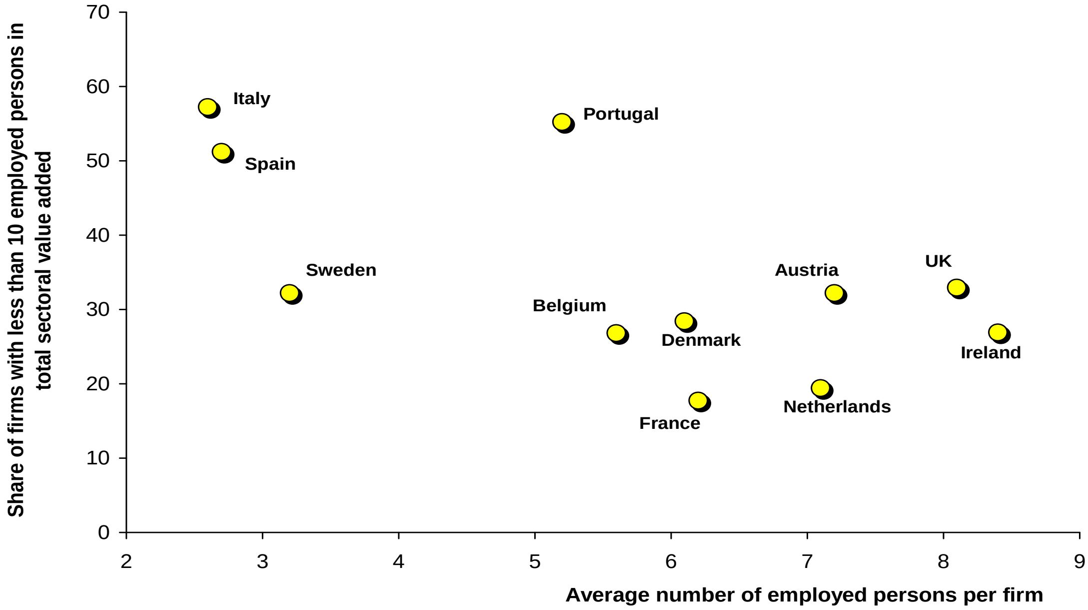
* A slightly revised version of this chapter, co-authored by Henk Kox and Henry van der Wiel, was published as Chapter 11 in 'Business Services in European Economic Growth', 2007, Palgrave McMillan Publishers, New York, US.

[1] Van der Wiel (2001; 1999) and Kox (2004, 2002).

- is the incidence of scale sub-optimality related to characteristics of the market or to national regulation characteristics?

The research with regard to these questions will be done mainly based on Eurostat NewCronos data. Section 7.1 presents some descriptive statistics for the business services for the 11 EU-countries. Section 7.2 of the paper sketches the analytical framework. After a brief data description in Section 7.3, Section 7.4 presents the empirical results with regard to the hypotheses. Section 7.5 summarizes the overall conclusions.

Figure 7.1 Average firm size in business services and the share of small firms (<10 employed persons) in total value added, 11 EU-countries, 1999



Note: NACE K72 + K74. Firms with less than 1 employed person are not included. Calculated from Eurostat NewCronos data (Firm demography, Business services by size class). Data for the Netherlands were compiled from Dutch production census data, using the New Cronos classification of size classes.

7.2 Stylized facts

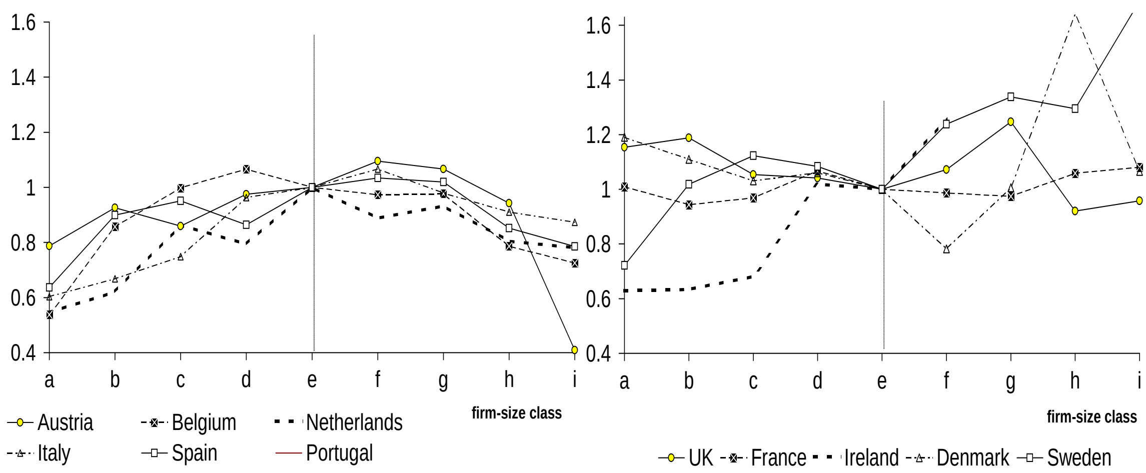
The business-services industry consists of a wide range of branches such as accountants, market research, economic consultancy, and industrial cleaning. Large differences in features are related to, among others, differences in labour intensity, capital intensity, knowledge intensity and product differentiation. The products of the business-services industry are mostly high value added products due to the large knowledge intensity of this industry. Business-services industry compared with other industries employs relatively many high-educated employees and employers. In order to limit the amount of sectoral heterogeneity, we focus on the labour-intensive part of the business-services industry.[2]

[2] We particularly focus on computer-related services (NACE K 72) and Other Business Services (NACE K74). We exclude two capital-intensive branches: real estate (NACE K70) and equipment rental (NACE K71). We have also left out the data for contract-research establishments (NACE K73), since this sub-sector appeared to include data for university institutes where education is an unobserved side-product.

At first glance, there are a number of similarities across the EU-countries with respect to some key statistics. Here, we mention two of them. First, business services in most EU-countries is typically a small-firm business with the average number of employed persons well below ten persons (see Figure 7.1). The figure however also shows that the share of firms with less than ten employed persons ranges between 17 and 57 per cent of total value added. This indicates that there can be large differences between countries in the firm size-distribution.

A second similarity across most EU countries is that average labour productivity level may differ considerably between size classes of firms. Figure 7.2 depicts the average labour productivity for all business services per size class and per country. In the left panel we see that six out of eleven countries display a clear hump-shape (inverted U) relation between the productivity level and firm size. The right panel shows that in two countries (Ireland, Sweden) there is a monotone productivity increase by size class, and in three countries (UK, France, and Denmark) the relation between labour productivity and scale does not show a clear pattern. Overall, the graphs suggest that scale effects could play a role in the productivity performance of firms. The hump-shape curvature hints at the existence of an optimal firm size. In the rest of the chapter we will further investigate the nature and causes of the different productivity performance by size class.

Figure 7.2 Relative labour productivity performance by size class in business services, 11 EU countries, 1999



Note: Relative labour productivity by size class (size class with 50-99 employees is benchmark) for all sub-sectors. Labour productivity is measured as value added (in 1000 Euros) per employed person. Legend for firm-size classes, based on employed persons per firm: a) 1-4; b) 5-9; c) 10-19; d) 20-49; e) 50-99; f) 100-249; g) 250-499; h) 500-999; and i) over 1000 employed persons

7.3 Explanatory models

In this section, we describe the explanatory models that will be tested to locate scale effects in business services, and their main assumptions. Our basic framework is a translog production function. First, we discuss the specification of our basic model. Scale effects are here considered only from a technological perspective. Next, we widen the perspective of the translog function by augmenting it with variables that control for market-specific factors and country-specific policy factors. Finally, we introduce the main characteristics of a distance-to-frontier model. We apply the generalised stochastic frontier approach of Kumbhakar et al. (1991) that simultaneously explains X-inefficiencies and input intensities from market-specific and country-specific characteristics.

a) Basic production function (PF) model

The presence of scale effects means that an output increase (*ΔOUT*) is not only a function of increased inputs (*ΔIN*) but also from the already achieved level of inputs (*IN*):

$$\Delta OUT = f(\Delta IN; IN) \tag{1}$$

The effect of the marginal unit of inputs on output growth is variable with the already attained level of inputs. If the long-run average-cost function of a firm in an industry displays a U-shape, then the production elasticity of at least one input must be variable. The occurrence of variable or "local" scale effects can for instance occur when there are discontinuities in the technology options, lower efficiency incentives (bureaucracy), or less facilities for internal labour division. It implies that some firm sizes allow more efficiency than other sizes.

To take into account variable input elasticities, we employ the so-called translog production function in which the expansion of one or more inputs may have a non-linear effect on the output level.[3] The translog specification explicitly checks for variable scale effects and the presence of size-class specific complementarity between inputs. The presence of variable scale effects is detected separately by adding a quadratic term for each input.[4] In a logarithmic specification the basic translog production function for a firm's value added reads:

$$\ln Y = \alpha_y + \beta_1 \ln K + \beta_2 \ln L + \tfrac{1}{2}\beta_{11}(\ln K)^2 + \tfrac{1}{2}\beta_{22}(\ln L)^2 + \beta_{12}(\ln K \times \ln L) \tag{2}$$

in which Y is value added, K is physical capital inputs, and L represents labour inputs. The parameters β_1 and β_2 reflect the linear effects of more input use on value added. The parameters

[3] Cf. Christensen et al. (1971); Fuss et al. (1978); Greene (1993); Kim (1992) and Ray (1998).

[4] This is done by introducing a second-order Taylor expansion and parametrising for the quadratic effects of input use. With two inputs, capital (K) and labour (L), the partial derivatives of output with respect to both inputs are evaluated around the sample mean.

β_{11} and β_{22} reflect the non-linear effects for both basic inputs. Interaction parameter β_{12} represents local level interactions between the individual inputs.[5] The interaction parameter becomes significant if the output elasticity of a particular input depends on the *level* of the other input (input complementarity). As an example for the business-services sector, we may think of the positive labour productivity effects that come within reach after a fixed-capital investment in a local PC network. The constant α_y is a catch-up term for the impact of non-observed variables on output, frequently interpreted as the level of ”multi-factor productivity”. In the basic specification we add sector and country dummies that account for unobserved sector-specific and country-specific fixed effects.

Measuring economies of scale. With regard to scale effects on production, three meaningful outcomes for the model described by equation (2) can be distinguished. When there are no scale effects (constant returns to scale) we will find that $\beta_1 + \beta_2 = 1$, i.e. the output increase is equal to the increment of combined inputs. There may also be identical scale effects – either diminishing or increasing – for all firm-size classes. That is the case when we find the combination of $\beta_1 + \beta_2 \neq 1$ with $\beta_{11} = \beta_{22} = \beta_{12} = 0$ (no variable scale and input-interaction effects). Finally, if significant non-zero values are found for β_{11}, β_{22} and/or β_{12} it means that differentiated scale effects occur for specific size classes of firms.[6]

b) Augmented PF-model

In the basic translog specification, it is assumed that the shape of the production function and therefore the scale effects are identical everywhere: for all firms in all sub-sectors of business services in all EU-countries. This is a simplification as there may be other factors that play a role in specific sub-sectors and in specific countries. We therefore augment our basic translog PF-model with variables that control for market structure and country-specific policy factors.

We distinguish three market-specific factors that may influence the relation between scale and productivity: market segmentation, market concentration, and the degree of product homogeneity. We subsequently discuss each of these factors.

Market segmentation implies that not all firms in a sub-sector are direct competitors of each other. The existence of market segmentation has potential repercussions for the competitive incentives to remove scale-related inefficiencies. There are some suggestions in the literature that business-services markets may be segmented (at least partly) along firm-size characteristics, and that this is to some extent related to reputation effects.[7] We use a simple procedure to control for the possible impact of firm-size related market segmentation on productivity.

---

[5] The cross derivatives in (2) are assumed to be symmetric: $\beta_{ij} = \beta_{ji}$ *for* $i \neq j$. Note that by imposing zero restrictions on each of the coefficients β_{ij} $(i,j = 1,2)$ the translog production function reduces to a standard Cobb-Douglas production function.

[6] The type of scale economies that prevail can be measured by adding up the derivative of output with respect to the inputs of capital, respectively labour.

[7] See O’ Farrell and Moffat, 1991; CSES 2001; Kox, 2002.

Suppose size-related market segmentation is present. In that case, the firm's input choices that govern productivity performance will be geared more towards competition in its own size segment than towards competition with firms in other size-segments of the market. As the measure of competition we take the average firm's market share; this is the inverse of the number of firms (*NOF*) in a relevant market. When segmentation by size class is present, the number of competitors in the firm's own size-class (*SEGM*) will have a stronger impact on the firm's productivity performance than the number of competitors in the rest of the sector's size classes (*SR*). For size class *s* (*s=1,...,S*), sector *j* (*j=1,..,J*) and country *k* (*k=1,..,N*) the normalized indicators for intra-segment competition intensity and extra-segment competition intensity are:[8]

$$SEGM_{sjk} = \ln\left(\gamma_{jk}\ NOF_{sjk}\right) \text{ and } SR_{sjk} = \ln\left\{\gamma_{jk}\ (NOF_{jk} - NOF_{sjk})\right\} \tag{3a}$$

$$\text{with } \gamma_{jk} = \frac{\frac{\gamma_k}{J}\sum^J NOF_{jk}}{NOF_{jk}} \text{ and } \gamma_k = \frac{\frac{1}{N}\sum^N NOF_k}{NOF_k} \tag{3b}$$

The segmentation hypothesis can be tested straightforwardly by adding both variables to the production function model. If α_1 and α_2 are respectively the impact parameters of, respectively, $SEGM_{sjk}$ and SR_{sjk} in the augmented production-function model, the interpretation of the results must be as follows. If *all* firms in the sub-sector compete with each other, regardless of size segment, the parameter α_1 will either be zero or be roughly equal to the parameter α_2. If, however, market segmentation by size class is important, then we will find: $|\alpha_1| > |\alpha_2| > 0$. Given the possibility that one of both parameters could directly pick up scale inefficiencies, we apply the segmentation test in an absolute formulation.[9]

Market concentration is a second market characteristic that we want to control for. High concentration implies that imperfect competition prevails in a market, with less pressure on firms to remove scale-related X-inefficiencies, even if markets are not segmented. Fabiani et al. (2005) and ECB Task Force (2006) find that European non-trade services firms review and change prices less often than in other industries, indicating the presence of mark-up pricing and imperfect competition. With a higher competition intensity, firms have less opportunities for mark-up pricing, and firm size will be more directly related to their cost and labour productivity

[8] Since we want to apply the model to cross-section data for different sub-sectors and countries, the normalisation factor γ_{jk} is necessary to remove the impacts on the total number of firms per sub-sector that come from relative country size and relative sector size (within a country). Normalisation makes both indicators comparable across countries and markets.

[9] The test can also be put in a strong form, i.e. $\alpha_1 > \alpha_2 > 0$, but this fails in case of opposite signs. In the case of excessive entry, the average firm's market share could become smaller than minimal efficient scale, thus depressing the size segment's average productivity and producing a negative sign for one of both parameters.

levels. We want to control for this possibly disturbing effect on our results. We use (the logarithm of) the Hirschmann-Herfindahl index (*HHI*) as a measure of market concentration. It does not measure competition intensity as such, but it may indicate markets with weak incentives for eradicating scale-related inefficiencies.[10] A high degree of market concentration is expected to cause a lower efficiency pressure. Hence, we expect a negative sign for the estimated *HHI* parameter.

Finally, the degree of *product differentiation* is a final market characteristic that we want to take into account. Descriptive data for business-services industry in the EU show that some sub-sectors have a high degree of product differentiation. Product differentiation may affect the input mix and the internal organization of firms. In case of product differentiation, labour-saving and internal division of labour according to the Babbage principle (spreading costs of overhead and management labour over more workers) may get more difficult, thus affecting productivity. Product specialisation in business services could have two opposite effects on productivity. The required higher overall qualification level of employees may benefit labour productivity in some elements of the production process. Conversely, the lack of task standardization, specialization and production routines may negatively affect productivity.[11] A *priori,* it is not obvious which of both productivity effects is dominant. To isolate the potential impact of product differentiation on productivity, we add sub-sector dummies to take account of product differentiation and other unobserved factors that vary by sub-sector.

Apart from market characteristics, the augmented production-function model also accounts for *country-specific differences* in product-market regulation. Regulation of product markets by national governments could possibly explain part of the variation in business services productivity across the EU-countries. Stricter regulations are found to go along with more mark-up pricing in services (ECB Task Force, 2006); hence, with strict regulations there will be fewer incentives to remove scale-related inefficiencies. Also research by Scarpetta et al. (2002) and Schiantarelli (2005) supports the expectation that the incidence of scale inefficiencies may be a function of the regulation type and the relative regulation intensity in countries. We explicitly control for two types of national policy indicators:[12]

- intensity of product-market regulation, relative to other countries (*PMR*). We expect this variable to correlate negatively with productivity.

---

[10] The use of more preferable indicators of competition-intensity like the relative profit measure (cf. Boone 2000) or average price-cost margins is problematic in our case because price and cost data are difficult to obtain for European business services.

[11] If branches with a high degree of product differentiation on average have higher-qualified employees this might also mean that part of their jobs consists of elements for which they are over-qualified. It may thus have a negative impact on cost efficiency.

[12] It turned out that other available indicators such as the national restrictions on foreign direct investment strongly correlate with other explanatory variables.

- entry costs for new firms (*EC*). A high entry hurdle diminishes the competitive pressure that newcomers in the market exert on incumbent firms. We expect a negative effect on average firm productivity.

With the addition of market-specific and country-specific regulation factors to equation (2), we arrive at the augmented translog PF-model. Since we focus on labour productivity, the equation is further reformulated so that labour productivity is indeed the dependent variable:

$$\ln(\frac{Y}{L}) = \lambda_L + \beta_1 \ln K + (\beta_2 - 1)\ln L + \frac{1}{2}\beta_{11}(\ln K)^2 + \frac{1}{2}\beta_{22}(\ln L)^2 + \beta_{12}(\ln K \ln L)$$
$$+ \alpha_1 SEGM_{sjk} + \alpha_2 SR_{sjk} + \alpha_3 HHI + \alpha_4 PMR + \alpha_5 EC + \mu \qquad (4)$$

All β-parameters refer to technological parameters, whereas the α-parameters refer to the control variables of the augmented model. *SEGM* and *SR* are the indicators for within-segment competition respectively competition with other segments, while *HHI* denotes the market concentration. Both are specific for sub-sector and country. Furthermore, two indicators refer to country-specific policy regulations: product market regulation (*PMR*) and Entry costs (*EC*). Vector *D* contains sub-sector dummies that account for unobserved sector-specific fixed effects. Finally, λ_L is the regression constant, and μ is the error term of the regression. An important element of the (augmented) PF-model is that the error term μ is thought to contain only white noise.[13]

c) Distance-to-the-frontier model

The production function models assume a representative "average" firm with a more or less homogenous input mix. Here we take up the issue of heterogeneity by applying a distance-to-frontier approach. If data on input prices were available, it would be possible to follow the 'dual' approach of Balk (1998) and Balk and Van Leeuwen (1999), which enables a distinction between technical inefficiency (a certain level of output could be attained with less inputs of given price) and allocative inefficiency (costs could be reduced by better taking into account the prices of different inputs). However, data on prices are not available. Therefore, we have chosen to adopt the 'primal' (production function) approach to frontier modelling. The distance-to-frontier model does two things. It identifies a technological efficiency frontier per sector ("best practice").[14] All individual observations can thus be defined as deviations from the frontier. The model at the same time explains from market-structure variables and regulation characteristics

[13] The errors are assumed to be i.i.d. normally distributed around mean zero, $\mu \sim N(0, \sigma_\mu^2)$, i.e. they can have positive or negative values.

[14] Technically, the efficiency frontier is the set of all minimum input combinations needed to produce a particular output level. The efficiency frontier is equal to a theoretical production function that identifies all output-maximising (or input-minimising) combinations of inputs and output.

why some or even most firms are not on the efficiency frontier. The individual productivity distance to the frontier firm (X-inefficiency) becomes the independent variable. We use the generalised stochastic frontier (GSF) model, an adapted version of the method developed by Kumbhakar et al. (1991). The GSF takes into account that both X-inefficiencies and input choices depend on market-specific and country-specific characteristics. The first part of our GSF-model is again a standard translog productivity equation:

$$\begin{aligned}\ln\left(\frac{Y}{L}\right) = {} & \lambda_L + \beta_1 \ln K + (\beta_2 - 1)\ln L + \frac{1}{2}\beta_{11}(\ln K)^2 + \frac{1}{2}\beta_{22}(\ln L)^2 \\ & + \beta_{12}(\ln K \times \ln L) + \delta B + \varepsilon\end{aligned} \tag{5}$$

The vector B collects the sector-, country- and size-class dummies that act as control variables for the technology parameters. The error term ε is important for further analysis in the GSF-model, since it is thought to contain a deterministic component (τ), which represents the part of the X-inefficiencies that can be explained from market and regulation characteristics. Apart from that, a white noise component (ω) is present, so that $\varepsilon = \tau + \omega$.[15] The efficiency frontier is defined as those observations without deterministic X-inefficiencies, so that the distribution of τ is truncated at zero (condition $\tau \leq 0$). The second equation of the GSF- model explains the X-inefficiencies in terms a vector Z that contains the market and regulation variables:

$$\tau = \gamma' Z + \theta \qquad \text{with} \quad \tau \sim N(\gamma' Z, \sigma_\tau^2) \tag{6}$$

Equation (6) expresses that X-inefficiencies are drawings from a truncated normal distribution with expectation $\hat{\tau} = \hat{\gamma}' Z$. This specification implies that X-efficiencies are deviations from their mean determined by the vector Z.[16] The market and regulation variables in Z are the same as those used in the augmented PF-model. The parameters of the two equations of the GSF model, (5) and (6), are to be estimated simultaneously. Note that, because the last equation explains *in*efficiencies, the signs of the estimates for the explanatory variables of (6) must be interpreted in an opposite way (negatively) to find the impact on labour productivity.

The three explanatory models that have been developed in this section are related to each other. They can be considered as stages in diminishing abstraction: the first model (PF) explains possible scale effects only from technological input choices. The second model (augmented PF) allows for the possibility that market characteristics and country-specific regulatory characteristics can affect productivity, and hence can be a source of scale effects. Both models

---

[15] The white noise component in the error term (ω) is again assumed to be i.i.d. normally distributed around mean zero: $\omega \sim N(0, \sigma_\omega^2)$. Moreover, τ and ω are assumed to be independent. i.e. $E(\tau, \omega) = 0$.

[16] In a companion paper we show the derivation of the likelihood function for the GSF model (Kox et al. 2007).

basically assume homogeneity of all firms, i.e. some representative firm. This homogeneity assumption is dropped in the GSF -model, by identifying a production frontier and explaining the individual firm's deviation to this frontier in terms of market characteristics and country-specific regulatory characteristics. The three models are tested subsequently.

7.4 Data

In order to test our explanatory models empirically we use national production census data for business-services firms, made available through the Eurostat NewCronos database *Firm demography, Business services by size class* (data retrieval august 2005). The data are for 11 EU member states and cover some 1.9 million individual firms, split up by sub-sector and by country, with the reference year 1999.[17] The data are aggregated by size class of firms, but since the number of firms by size class is given, we can infer data for the average firm by size class, by sub-sector and country. The aggregation level of the NewCronos data does not allow us to deal with firm-level heterogeneity, but we may calculate scale effects for the average firm in each size class in each sub-sector of the business-services industry.

Firm size is measured by the number of employed persons per firm, a measure that includes the entrepreneur. Nine different size classes are distinguished ranging from small firms with one to four employees to very large firms with more than 1000 employees. The available data allow a cross-section regression for 11 EU-countries: Austria, Belgium, Denmark, France, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. The total number of observations is about 760, from up to 12 different sub-sectors of NACE 72 (computer-related services) and NACE 74 (Other business services).

Labour input is measured as the number of employed persons. The amount of depreciation is used as an indicator for capital input. For market concentration, we use a modified version of the HHI.[18] For the variable PMR (intensity product-market regulation) we use the OECD's economy-wide indicator for the relative intensity of competition regulation in reference year 1998 (Nicoletti et al. 2000). A high value of the PMR indicates a relatively regulated national economy. Data for variable EC (policy-caused, country-specific costs for setting up a new firm) are derived from a World Bank dataset (Djankov et al. 2002). A high value of the indicator refers to a large amount of entry costs.

[17] Lacking data for the Netherlands have been compiled directly from Dutch production census data, ensuring compatibility by the use of the NewCronos aggregation method.
[18] In order to avoid multi-collinearity with the *SR* variable, we have calculated the *HHI* as the logarithm of summed squares of all size-class shares in a sub-sector's total value added.

Table 7.1 Estimation results for basic and augmented PF-model based on pooled regression in business services (all sub-sectors, 11 EU-countries, reference year 1999)

		Basic PF-model		Augmented PF-model	
	Parameter	Estimate [c]	T [a]	Estimate [c]	T [a]
Technology variables					
Fixed capital	β_1	0.51	5.5***	0.35	3.0***
Labour input	β_2	0.63	5.9***	0.60	4.3***
Local scale effects, capital-based	β_{11}	– 0.09	–3.9***	– 0.09	–3.8***
Local scale effects, labour-based	β_{22}	– 0.05	–1.7*	– 0.08	–2.5**
Local scale effects, capital-labour interaction	β_{12}	0.06	2.4***	0.09	3.7***
Size-class dummies					
1-4 employed persons				0.13	1.0
5-9 employed persons				0.02	0.2
10-19 employed persons				0.03	0.4
20-49 employed persons				0.06	1.0
50-99 employed persons				0.01	0.2
250-499 employed persons				0.05	0.8
500-999 employed persons				–0.12	–1.3
>1000 employed persons				–0.09	–1.0
Market-characteristics					
Within-segment competition ($SEGM_{sjk}$)	α_1			–0.06	–3.1***
Competition with non-segment firms (SR_{jk})	α_2			0.08	3.6***
Market concentration, (HHI)	α_3			–0.15	–3.6***
National policy regulation					
Product-market regulation (PMR)	α_4			0.06	1.7*
Entry costs (EC)	α_5			–0.54	–4.6***
Sector dummies [b)]		Yes		Yes	
Country dummies [b)]		Yes		No	
Other regression statistics					
Regression constant	α_y , λ_L	3.15	8.5***	4.49	7.5***
Number of observations		713		713	
Adjusted R^2		0.63		0.61	
Log likelihood		– 176.69		–216.6	

Notes: a) Asterisks denote the confidence interval (two-tailed) of the estimates: *** at 1% level, ** at 5% level, and * at 10% level. b) The size reference group is size class 100-249 employed persons, the reference sector is sub-sector NACE K744, and the reference country is Ireland. c) The use of size-class averages (based on different numbers of firm observations) could create a bias if we used Ordinary Least Squares estimation. To prevent this we apply the Weighted Least Square method with Heteroskedasticity-consistent standard errors.

7.5 Empirical results

We subsequently present the estimation results for the explanatory models, starting with the results for the two PF-models. The dependent variable is in all cases the logarithm of the productivity level (value added per employed person).

Table 7.1 presents the results of both the basic and the augmented PF-model applied on the pooled dataset for all 11 EU-countries and all available sub-sectors. The results for the basic PF-model suggest that there are increasing returns to scale in the EU-business-services industry. From the magnitude of the technology variables in combination with the levels of capital and labour inputs (not shown) it can be inferred that there are positive scale economies. Since β_{11}, β_{22} and β_{12} are significantly different from zero, we must conclude that these positive scale effects are "local", i.e. they only occur in some size classes.

We would expect these local effects to pop up in the augmented PF-model where we add dummies for individual size classes as well as variables for market characteristics and country-specific regulation characteristics. However, the estimation outcomes show that none of the size dummies is statistically significant. This suggests that neither small nor very large firms operate on a less-efficient production frontier scale. A small average market share for firms within a size segment (variable *SEGM*) has a significantly negative impact on labour productivity, but overall this effect is dominated by a larger positive productivity impact of competition with firms in other size segments (variable *SR*). Because of the relative size of both effects, the market segmentation hypothesis is rejected in the augmented PF-model: the condition $|\alpha_1| > |\alpha_2|$ is not fulfilled. The estimated coefficients of the market concentration (*HHI*) and policy-caused entry costs (*EC*) have the expected negative sign and are statistically highly significant. The *PMR* variable is significant at the 10 per cent confidence level, but it has not the expected sign. The positive sign suggests that strict regulation in a country strengthens labour productivity performance. This is at odds with most of the literature, and we do not have a good explanation for this result. The indicator for the intensity of product-market regulation in a country could be too broad to be meaningfully used for explaining the differences in productivity level of the business-services industry.

Both of the preceding models illustrate that capital intensity (parameter β_1) matters for the labour productivity level in business services. The coefficient for capital is, however, much smaller in the augmented PF-model. The 'local effect' parameter β_{11} indicates that capital intensity has decreasing returns to scale in some size classes.

Results for the GSF-model

The basic PF-model and its augmented variant pay no attention to the possibility that firms are heterogeneous in their input mix, and that not all of them operate on the efficiency frontier. The results of the GSF-model indicate that it is important to take firm heterogeneity and X-inefficiencies on board. The model simultaneously explains X-inefficiencies and input intensities from market-structure variables and regulation characteristics. Table 7.2 presents the results for this model.

Table 7.2 Estimation results for GSF-model based on pooled regression in business services (all sub-sectors, 11 EU-countries, reference year 1999)

	Parameter	Estimate [c]	T [a]
Production frontier equation			
Technology variables			
Fixed capital	B_1	0.42	6.3***
Labour input	B_2	0.67	7.3***
Local scale effects, capital-based	B_{11}	– 0.08	–3.7***
Local scale effects, labour-based	B_{22}	– 0.05	–2.0**
Local scale effects, capital-labour interaction	B_{12}	0.06	2.8***
Size-class dummies			
1-4 employed persons		–0.36	–5.2***
5-9 employed persons		–0.32	–4.5***
10-19 employed persons		–0.21	–3.0***
20-49 employed persons		–0.03	–0.4
50-99 employed persons		–0.01	–0.1
250-499 employed persons		–0.01	–0.1
500-999 employed persons		–0.04	–0.4
>1000 employed persons		0.03	0.3
Sector dummies[b)]		Yes	
Country dummies[b)]		Yes	
X-inefficiencies equation			
Market-characteristics			
Within-segment competition ($SEGM_{sjk}$)	A_1	–0.31	–1.8*
Competition with non-segment firms (SR_{sjk})	A_2	0.15	0.9
Market concentration (HHI)	A_3	–0.03	–0.2
National policy regulation			
Product-market regulation (OECD)	A_4	0.06	0.3
Entry costs (OECD)	A_5	1.88	1.7*
Size-class dummies [b)]		Yes	
Other regression statistics			
Regression constant	λ_L	3.67	13.0***
Number of observations		713	
Log likelihood		– 112.13	

Notes: a) Asterisks denote the confidence interval (two-tailed) of the estimates: *** at 1% level, ** at 5% level, and * at 10% level. b) The size reference group is size class 100-249 employed persons, the reference sector is sub-sector NACE K744, and the reference country is Ireland. c) Both equations of the GSF model have been estimated simultaneously.

From the estimated technology parameters and the input levels (not shown) we may conclude that business-services industry is characterised by increasing returns to scale, once we control for the possibility of X-inefficiencies. Particularly, the linear parameters for capital inputs (β_1) and labour inputs (β_2) are substantially larger in the GSF-model than in the augmented PF-model. The parameters for the non-linear input effect (β_{11}, β_{22} and β_{12}) are significantly different from zero, indicating that there are "local" scale effects, specific for some size classes. The estimates for the size-class dummies, now allows us to identify the locus of these local scale effects. Small firms, up to a size of 20 employed persons, experience considerable productivity disadvantages compared to the reference size class (100-249 employed persons). The findings suggest that firms operate on different production frontiers. Recall, that Figure 7.2 already suggested that such a pattern prevails for a considerable part of European business-services industry.

However, the GSF results do not fully confirm the hump-shape pattern in the size-productivity relation (left panel Figure 7.2). The estimates for the largest size classes turn out not to be significantly different from zero. A possibly explanation is that larger firms can, on average, compensate a relatively lower labour productivity by a more efficient use of capital inputs. Scale-related productivity effects only occur up to a threshold firm size. A number of 20 employed persons appears to be the minimum efficient firm size in European business services. Beyond a size of 20 employed persons further firm growth on average yields no more significant productivity advantages, if we control for capital input. The reasons for this minimum firm size can be related to internal labour division (in the spirit of Adam Smith's pin factory), human capital specialisation, spreading fixed capital costs, routine development, and the Babbage principle (possibilities for spreading managerial and other overhead costs). Further research would be necessary to assess which of these factors forms the binding constraint that defines the minimum efficient scale in business services.

While scale-related inefficiencies are primarily found at firm sizes smaller than 20 employed persons, X-inefficiencies related to sub-optimal input choices may also occur at larger firm sizes. The τ-equation of the GSF-model identifies the market characteristics and regulatory environments that tend to be correlated with X-inefficiencies. Size-related market segmentation could be an important characteristic in business-services markets. The market segmentation test $|\alpha_1| > |\alpha_2|$ is satisfied.[19] The estimated parameter is significant at the 10 per cent confidence level; hence the issue warrants further research.

There is a remarkable difference with Table 7.1. Now that X-inefficiencies are taken into account, the estimated parameter for intra-segment competition (*SEGM*) has a larger value and a different sign. More intra-segment competition has a negative impact on *in*efficiencies, and hence a positive impact on labour productivity. Being in a "crowded" size segment of the market could therefore to some extent compensate any scale-related inefficiencies. Consistent with this is the finding that a high level of policy-caused start-up costs for new firms (*EC*) works out positively on the incidence of X-inefficiencies, and hence negatively on the labour productivity performance. A final result is that, on average, market concentration (*HHI*) and the intensity of competition-related regulation (*PMR*) are not significant factors for explaining the incidence of X-inefficiencies.

[19] The estimated parameter for α_1 is significant at the 10 per cent confidence level (2-tailed), while α_2 is not statistically significant.

7.6 Conclusions and some policy implications

We find clear indications for the existence of increasing returns to scale in business-services firms. The scale effects are not the same for all size classes. Throughout the EU, firms with less than 20 persons have significantly lower average labour productivity levels than the rest of the business-services industry. The size of 20 employed persons can be regarded as the minimum-efficient scale in European business services. Beyond that size there are no significant impacts of scale on labour productivity performance.

Likely explanatory candidates for the presence of the minimum-efficient scale size in business services are traditional drawbacks of small scale known from the literature, such as having less efficient division of labour, and having less opportunities for spreading fixed managerial costs, overhead costs, fixed human-capital costs, and fixed-capital costs. Further research could establish the reasons for the presence of the minimum-efficient scale size. Apart from scale-related inefficiencies, we find evidence that X-inefficiencies related to input choices may occur in all size classes. Estimation results for the generalised stochastic frontier model (GSF) indicate that X-inefficiencies caused by sub-optimal input choices are affected by market characteristics and the regulatory environment of firms. In particular we find that business-services markets may be segmented by size class of firms. This means that firms from different size classes on average only have weak competition with firms in other size classes. Small firms hardly compete with large firms and vice versa. They possibly serve different market segments, have different clients and also different types of products.

A final result is that more intra-segment competition works out positively on labour productivity of the firms in that size class. Being in a "crowded" size segment of the market could thus to some extent compensate scale-related inefficiencies. For instance, the relatively intense "neck-and-neck" competition among small firms may to some extent both compensate their scale-related inefficiencies, for instance, by reducing their non-scale inefficiencies including suboptimal input choice. Consistent with this is the finding that a high level of policy-caused start-up costs for new firms negatively affects the labour productivity performance. Higher entry barriers may weaken the stimulus for incumbent firms to be efficient.

Our results are based on cross-section analysis for one year, but we think the results warrant a more comprehensive research programme on scale-effects in European business services, using data on more years (panel data) and real micro-level data instead of size-class averages. In fact such research is already long overdue, if we take into account that business services is one of the largest sectors in the European economy with an employment share of about 11 per cent, a value-added share of about 12 per cent in the European Union, and a 54 per cent share in EU employment growth between 1979 and 2001.

Although we cannot discuss policy implications at length, there are several links between the productivity agenda in business services and government policies in EU countries. Government policies have leaned strongly towards promoting market entry by new entrepreneurs, rather than paying attention to existing scale inefficiencies. The idea was that more entry is good for competition is probably right. Entry by new business-services firm constituted was a major factor major in total EU employment growth during the 1990s. This was (partly) the result of government policies. For the future, further thought must be given to such policies before continuing on the same track. When market segmentation is indeed as important as we think it might be, new entrants will mostly compete with each other, i.e. with the other small and 'young' firms.[20] Like with lobsters that try to escape the box in which they are, their mutual competition means that no one gets out. They may remain operating at a relatively inefficient firm size.

Maybe a new balance has to be struck between 'upscaling' in order to remove scale inefficiencies and ensuring a constant influx of new entrepreneurs. The question is whether the markets themselves will solve this issue, or whether the governments have a role to assist the market forces. With segmented markets – both within and between countries– competition may not automatically lead to more scale-efficient production sizes. Many national and EU policy programmes nowadays play at least lip service to lowering administrative burdens for firms. Perhaps especially the firms below 20 employed persons should get a light administrative burden from government regulation. This will make it easier for firms to grow beyond the present small-firm business model. In addition, the opening of markets for intra-EU competition may yield more incentives for 'upscaling' of business-services firms.

References

Aghion, Ph. and R. Griffith, 2005, *Competition and growth: reconciling theory and evidence*, MIT Press, Cambridge MA.

Babbage, C., 1835, *On the economy of machinery and manufactures*, 4th edition, London.

Balk, B.M., 1998, *Industrial Price, Quantity, and Productivity Indices: The Micro-Economic Theory and an Application*, Kluwer Academic Publishers, Massachusetts, USA.

Balk, B.M. and G. van Leeuwen, 1999, Parametric estimation of technical and allocative efficiencies and productivity changes: a case study, in: S. Biffignandi (ed), *Micro- and macrodata of firms - statistical analysis and international comparison*, Physika Verlag, Heidelberg, p. 319-347.

Boone, J., 2000, Competitive Pressure: The Effects on Investment in Product and Process Innovation, *Rand Journal of Economics*, vol. 31 (3), pp. 549-569.

Christensen, L.R., D.W. Jorgenson and L.J. Lau (1971), "Conjugate duality and the transcendental logarithmic production function," *Econometrica* 39, 255-256.

CSES, 2001, Barriers to trade in business services - Final report, Report commissioned by the

[20] Cf. the "neck-and-neck" competition in Aghion and Griffith (2005).

European Commission, Centre for Strategy & Evaluation Services / European Commission, Brussels.

Djankov, S., R. La Porta, F. Lopez, and A. Shleifer (2002), The regulation of entry, *Quarterly Journal of Economics*, vol. 117 (1), pp 1-37

Eurostat, 2004, *Business services - an analysis of structural, foreign-affiliates and business-demography statistics*, European Commission/ Eurostat, Luxembourg.

Fabiani, S., M. Druant, I. Hernando et al., 2005, The Pricing Behaviour of Firms in the Euro Area: New Survey Evidence, Working Paper Series No. 535, European Central Bank, Frankfurt.

Fuss, M. and D. McFadden (eds.), 1978, *Production economics: a dual approach to theory and applications*, North-Holland, Amsterdam.

Greene, W.H., 1993, *Econometric analysis*, 2nd ed., Prentice Hall, Englewood Cliffs.

Kim, H.Y., 1992, The translog production function and variable returns to scale, *The Review of Economics and Statistics*, volume 74, p.p. 546-552.

Kox, H., G. van Leeuwen and H. van der Wiel, 2007, Productivity, scale and market structure in European business services, CPB Discussion Paper No. XX, CPB, The Hague (forthcoming).

Kox, H., 2002, Growth challenges for the Dutch business services industry; international comparison and policy issues, Special study No. 40, CPB, The Hague.

Kox, H., 2004, The contribution of business services to aggregate productivity growth, in: G. Gelauff et al. (eds), *Fostering productivity: patterns, determinants and policy implications*, Contributions to Economic Analysis #263, Elsevier Science, June 2004, pp. 243-264.

Kumbhakar, S., S. Gosh, and J. McGucking, 1991, A Generalized Production Frontier Approach For Estimating Determinants of Inefficiency in US Dairy Firms, *Journal of Business and Economic Statistics*, vol. 9, pp. 279-286.

Nicoletti, G., S. Scarpetta, and O. Boylaud, 2000, Summary indicators of product market regulation with an extension to employment protection legislation, OECD Economic Department Working paper no. 226, Paris.

O'Farrell, P. and L. Moffat, 1991, An interaction model of business service production and consumption, *British Journal of Management*, vol. 2, pp. 205-221.

Paterson, I., M. Fink and A. Ogus, 2003, Economic impact of regulation in the field of liberal professions in different Member States - regulation of professional services, Study for the European Commission, Institute for Advanced Studies, Vienna.

Ray, S.C., 1998, Measuring scale efficiency from a translog production function, *Journal of Productivity Analysis*, volume 11, p.p. 183-194.

Scarpetta, S., Ph. Hemmings, T. Tressel and J. Woo, 2002, The role of policy and institutions for productivity and firm dynamics: evidence from micro and industry data, Economics Dept. Working Paper No. 329, OECD, Paris.

Schiantarelli, F., 2005, Product market regulation and macro-economic performance : a review of cross country evidence, IZA Discussion Paper No. 1791, Institute for the Study of Labor (IZA), Bonn.

Wiel, H.P. van der, 1999, Firm turnover in Dutch business services; The effect on labour productivity, CPB Research Memorandum No 159, CPB, Den Haag.

Wiel, H.P. van der, 2001, Innovation and productivity in services, CPB Report 2001/1.

Samenvatting (Summary in Dutch)

Innovatie en bedrijfsprestaties. Een verzameling van microdata studies

Dit proefschrift omvat een vijftal onderzoeken naar het belang van innovatie voor bedrijfsprestaties en één onderzoek waarin schaaleffecten in de bedrijfstak commerciële dienstverlening centraal staan. Met uitzondering van het laatste hoofdstuk werden de analyses uitgevoerd op bedrijfsgegevens die het CBS verzamelt voor het maken van statistieken. Een voordeel van het gebruik van dergelijke data is dat de gegevens betrekking hebben op de echte actoren in de economie en niet op uitkomsten voor bedrijfstakken of zelfs de gehele economie (zogenaamde macrodata).

Hoewel het belang van innoveren algemeen wordt erkend, bestaat er nog veel onduidelijkheid wat innoveren nu betekent voor – bijvoorbeeld – de ontwikkeling van de winstgevendheid of de productiviteit van bedrijven. De Nederlandse beleidsagenda is nog steeds sterk gericht op het verbeteren van de productiviteitsgroei in Nederland. Omdat er grenzen zijn aan de groei van de arbeidsinzet (o.a. als gevolg van demografische trends) wordt arbeidsproductiviteitsgroei in de toekomst steeds belangrijker voor het in stand houden van economische groei.

Uit macro-economische cijfers blijkt dat de productiviteitsgroei in Nederland in het afgelopen decennium is achtergebleven bij de Amerikaanse groeicijfers. Dit roept de vraag op of deze groeiachterstand te maken heeft met een relatief geringe innovatiekracht van het Nederlandse bedrijfsleven. Dat moge ook blijken uit het feit dat in verschillende macro-economische analyses de relatief lage intensiteit van de toepassing van informatie en communicatie technologie (ICT) in Nederland als een belangrijke oorzaak van de achterblijvende productiviteitsgroei wordt gezien.

Het hoeft geen betoog dat ICT in de achterliggende jaren tot een steeds belangrijker technologie is geworden. Bekende voorbeelden zijn de opkomst van internet en mobiele telefonie. In essentie is ICT een vorm van innovatie die belichaamd is in (het gebruik van) computers. In het jargon van economen: ICT is een vorm van in fysiek kapitaal belichaamde technologische vooruitgang. Voor de oorsprong van die vooruitgang moeten we verder teruggaan in de tijd en wel naar de jaren dat de microprocessor technologie door het bedrijf Intel werd ontwikkeld. De oorsprong van de aan ICT gerelateerde technologische vooruitgang ligt dus in essentie bij onderzoek en ontwikkeling (R&D) van ICT producerende bedrijven.

Bedrijven gebruiken ICT op uiteenlopende wijze. Dat gebruik begint bij het aanschaffen van (of het investeren in) computers en software. Investeren in computers en bedieningssoftware is echter geen voldoende voorwaarde voor het realiseren van productiviteitsgroei. Om ICT goed te laten functioneren moeten vaak complementaire kosten worden gemaakt voor zogenaamde niet-technologische innovaties. Veranderingen in bedrijfsorganisaties gericht op het uitbaten van de voordelen van het werken in (bedrijfsinterne) netwerken zijn hiervan een voorbeeld. De potentie om zowel interne als externe netwerkeffecten te genereren maakt dat computers als een speciaal type kapitaal kunnen worden bezien.

Het voorafgaande illustreert hoe de R&D van ICT producenten heeft geleid tot technologische innovaties in de vorm van nieuwe producten en productietechnieken die op hun beurt weer nieuwe innovaties (zowel technologisch als niet technologisch) kunnen genereren. Ook de introductie van internet is een voorbeeld van een dergelijk cumulatief innovatieproces, want zonder computertechnologie zou er geen internet of zelfs emailverkeer bestaan.

Het inzicht dat technologische vooruitgang 'maakbaar' is heeft geleid tot een nieuwe theoretische stroming in de economie, de zogenaamde endogene groeitheorie. De endogene groeitheorie beziet innovatie in brede zin als een belangrijk vliegwiel om economieën op een hoger groeipad te brengen. In hoofdstuk 1 bespreek ik de link tussen het onderwerp van dit proefschrift en de endogene groeitheorie. Uit die bespreking blijkt dat een veelbelovende tak van de endogene groeitheorie wordt gevormd door die stroming waarin de inzichten van Industriële Organisatie (IO) literatuur zijn geïntegreerd met het doel de endogene groeitheorie een betere theoretische onderbouwing en ook een hoger realiteitsgehalte te geven. Door het expliciet onderkennen van de wisselwerking tussen innovatie en concurrentie (marktwerking) en de rol van innovatie voor het vergroten van de kans op overleven of groeien wordt deze variant van de endogene groeitheorie ook wel aangeduid als de 'Schumpeteriaanse' endogene groeitheorie.

In essentie is de macroproductiviteitsgroei de resultante van een voortdurend proces van aanpassing aan 'best-practice' productietechnieken en de voortdurende strijd om marktaandelen tussen bedrijven. Bedrijven innoveren om sterker in de markt te staan, hetzij door het ontwikkelen van nieuwe producten of door het implementeren van slimmere (meer efficiënte) productiemethoden. Dit proces worden 'aangestuurd' door zowel in eigen beheer ontwikkelde innovaties als het imiteren of perfectioneren van innovaties die door andere bedrijven zijn ontwikkeld. Verder komt een deel van de macroproductiviteitsgroei voort uit het feit dat minder productieve bedrijven in de strijd om 'survival of the fittest' verdwijnen en plaats maken voor nieuwe en mogelijk productievere bedrijven. Achter de macrogroei gaat dus een zeer heterogeen proces van herverdelen van marktaandelen en productiemiddelen over bedrijven schuil. Dit verklaart waarom de belangstelling voor microdata voor het analyseren van de determinanten van productiviteitsgroei tegenwoordig zo groot is.

Het onderzoek dat in dit proefschrift wordt gepresenteerd maakt een veelvuldig gebruik van gegevens uit de Community Innovation Surveys (CIS). Deze databron geeft een uitgebreidere beschrijving van het innovatieproces dan de traditionele R&D enquêtes, die zich meer beperken tot het meten van de R&D uitgaven van bedrijven. In hoofdstukken 2 tot en met 4 wordt empirisch onderzoek gepresenteerd dat in belangrijke mate gebaseerd is op het gebruik van de microdata uit CIS. Die data worden ook gebruikt bij het onderzoek van hoofdstukken 5 en 6, maar spelen daar een minder prominente rol vanwege de nadruk op ICT als mogelijke drijvende kracht achter de productiviteitsgroei van bedrijven. De volgorde waarin verschillende onderzoeken in dit proefschrift zijn gepresenteerd hangt dan ook samen met het feit dat innovatie in de traditionele zin wordt opgevat als investeren in R&D en het gegeven dat ICT een relatief jonge technologie betreft.

Hoofdstukken 2 tot en met 4 onderscheiden zich ook van eerder onderzoek op het punt van de econometrische modellering. Van oudsher werd voor de modellering gebruik gemaakt van een model met slechts één vergelijking voor het beschrijven van het verband tussen R&D en productiviteitsgroei. In economenjargon wordt dit de productiefunctie aanpak genoemd. In de productiefunctie representeert R&D als het ware een aparte productiefactor met een eigen bijdrage aan de productiviteitsgroei naast de bijdragen van traditionele productiefactoren als arbeid, fysiek kapitaal (bijvoorbeeld machines en gebouwen) en intermediair verbruik (bijvoorbeeld energie of grondstoffen). De schatting van de coëfficiënt van de R&D variabele geeft dan informatie over de bijdrage van R&D aan de groei van de zogenaamde Totale Factor Productiviteit (TFP): de groei van de productie gecorrigeerd voor de verandering van de inzet van de andere genoemde productiefactoren.

Dit basismodel voor het kwantificeren van de bijdrage aan de productiviteitsgroei van innovatievariabelen is terug te vinden in de verschillende hoofdstukken van dit proefschrift. De uitbreiding ten opzichte van de empirische literatuur betreft het expliciet modelleren van innovatie als een afzonderlijk productieproces waarin R&D een input is voor de productie van nieuwe of verbeterde producten of productiemethoden, die op hun beurt weer bijdragen aan de TFP groei. In de econometrie staat deze aanpak bekend als ‘structureel modelleren’. In hoofdstukken 2 tot en met 4 wordt deze aanpak gevolgd om de bijdrage van R&D aan de productiviteitsgroei als het ware te ontbinden in twee stappen, die elk beschreven worden in aparte modelvergelijkingen. De eerste vergelijking onderzoekt het verband tussen R&D investeringen (of de totale innovatiekosten) en innovatieve output in de vorm van nieuwe of verbeterde producten. De tweede vergelijking is de hiervoor genoemde productiefunctie waarin R&D investeringen zijn vervangen door de innovatie output variabele uit de eerste vergelijking. Door beide vergelijking simultaan te schatten ontstaat een beter inzicht in de causale relatie tussen, bijvoorbeeld, investeren in R&D en productiviteitsgroei. Kort samengevat weerspiegelt dit model de idee dat niet elke Euro die in innovatie wordt geïnvesteerd ook werkelijk tot innovatiesucces leidt en dat de bijdrage van innovatie aan de productiviteitsgroei gemeten moet worden aan die innovatie-inspanningen welke wel succesvol zijn gebleken. Bovendien kan er in deze aanpak ook getoetst worden of andere factoren dan innovatiekosten van belang zijn voor het verklaren van verschillen in innovatieve output, bijvoorbeeld het belang van samenwerking op innovatiegebied of het gebruik van informatiebronnen bij innoveren.

De introductie van de hiervoor besproken innovatie productiefunctie als hulpmiddel voor het analyseren van het relatieve belang van de verschillende factoren die bij innoveren een rol kunnen spelen is terug te voeren op het werk van de bekende Amerikaanse econoom Griliches. De eerste empirische toepassing van zijn innovatie productiefunctie vinden we in onderzoek van Crépon, Duguet en Mairesse (CDM, 1998). Hoofdstukken 2 tot met 4 van dit proefschrift volgen de structurele aanpak van het CDM model, met dien verstande dat een aantal modificaties zijn aangebracht.

Hoofdstuk 2 combineert het basisprincipe van het CDM model met het klassieke 'Chain-Link' innovatiemodel van Kline en Rosenberg uit 1986 door het introduceren van een extra vergelijking voor de verklaring van verschillen in innovatiekosten tussen bedrijven en het introduceren van een terugkoppeling van bedrijfsprestaties naar innovatiekosten. Door deze modificaties kan niet alleen worden onderzocht of meer innovatie ook werkelijk leidt tot hogere omzetgroei maar tevens of hogere omzetten bedrijven ook prikkelen om meer te investeren in innovatie. Daarnaast is onderzocht of verschillen in innovatiekracht zich ook vertalen naar verschillen in werkgelegenheidsgroei. De resultaten van dit onderzoek wijzen o.a. op het bestaan van een significant positief verband tussen innovatieve output en omzetgroei en op een positief terugkoppelingseffect van omzetgroei naar innoveren. Anderzijds kon er geen positief innovatie-effect op de werkgelegenheid worden aangetoond.

Als we omzetgroei en werkgelegenheidsgroei aan elkaar relateren, geeft dit een eerste ruwe indicatie van (verschillen in) de productiviteitsgroei. De toevoeging 'ruw' verwijst hier naar het feit dat bij deze berekening geen rekening wordt gehouden met de bijdrage aan de groei van andere productiefactoren. Hoofdstuk 3 volgt een directere aanpak voor het verklaren van verschillen in productiviteitsgroei door het gebruik van betere productiviteitsmaatstaven. Verder richt dit hoofdstuk zich ook meer op de interpretatie van innovatie gedreven productiviteitsgroei. Als R&D investeringen of andere innovatiekosten daadwerkelijk leiden tot het creëren van nieuwe of verbeterde producten, dan leidt dit mogelijk tot een versterking van hun positie op afzetmarkten. Bij de verklaring van de productiviteitsgroei ontstaat dan het probleem dat de gemiddelde prijsontwikkelingen niet representatief zijn voor innoverende bedrijven. De innovatiebijdrage aan de productiviteitsgroei is dan niet een uitsluitend een reëel (volume) effect maar omvat dan mogelijk tevens een prijseffect omdat, afhankelijk van de mate van concurrentie, bedrijven voor nieuwe of kwalitatief betere producten aan afnemers een hogere prijs in rekening kunnen brengen. Dit aan marktwerking gerelateerde productiviteitseffect is in het model geïncorporeerd door het opnemen van een concurrentieparameter. De uitkomsten leiden tot een verwerping van de hypothese dat innoverende bedrijven opereren op markten met volledige concurrentie. De TFP groei van bedrijven hangt dus samen met de mate waarin bedrijven zich via productdifferentiatie onderscheiden van concurrenten. Verder blijkt dat dit effect sterker is als de omzet (bruto productie) als maatstaf voor de productie wordt gebruikt in plaats van de toegevoegde waarde (netto productie).

Hoofdstuk 4 presenteert een eerste poging tot ‘dynamisering’ van het CDM model. Door het opnemen van vertraagde innovatievariabelen is onderzocht of de mate van innovatie in een bepaalde periode samenhangt met de innovatie-inspanning in voorafgaande jaren. Het identificeren van dynamiek in innovatiegedrag is een moeilijk probleem en stelt hoge eisen aan de data. In hoofdstuk 4 is gebruik gemaakt van twee opeenvolgende innovatie-enquêtes, zodat het aantal waarnemingen in de tijdsdimensie op voorhand beperkt was tot twee. Bovendien ontstaan er gaten in de data omdat deze verzameld zijn via steekproeven. Informatieverlies kan echter ook gerelateerd zijn aan mogelijkheid dat bedrijven niet continue innoveren (het probleem van endogene selectie). Beide vormen van bedrijvenuitval kunnen tot gevolg hebben dat schattingsresultaten behept zijn met vertekeningen ten gevolge van selectiviteit. Die vertekening is gecorrigeerd door in het empirisch model selectievergelijkingen op te nemen. De belangrijkste conclusie van dit onderzoek is dat de persistentie van innoveren gemeten aan de outputkant van het innovatieproces kleiner is dan de persistentie gemeten aan de inputkant (innovatiekosten of R&D investeringen). Deze uitkomst is goed te duiden daar innovatiekosten voor een belangrijk deel bestaan uit een vaste component in de vorm van arbeidskosten (voor R&D personeel) terwijl, anderzijds, bedrijven er blijkbaar niet in slagen (of met goede redenen niet ervoor kiezen) om elk jaar weer nieuwe of kwalitatief betere producten op de markt te brengen.

Hoofdstukken 5 en 6 onderscheiden zich van de daaraan voorafgaande hoofdstukken in de zin dat innoveren betrokken wordt op investeren in ICT middelen. Wat ICT doet voor de productiviteitsgroei van bedrijven is nog steeds een belangrijk onderwerp van onderzoek. Diverse analyses kiezen daarbij de groeiboekhouding als uitgangspunt. Groeiboekhouden is de standaardmethode van macro-economen om langs ‘boekhoudkundige’ weg de bijdragen van verschillende productiefactoren aan de economische groei in kaart te brengen. Deze methodiek wordt meestal toegepast op macrodata. Door ICT als een aparte productiefactor op te nemen onderzoekt men of meer ICT kapitaal per werknemer ook werkelijk leidt tot een toename van de arbeidsproductiviteit (de bijdrage van ICT kapitaalverdieping). In veel gevallen blijkt dit zo te zijn. Een uitkomst die op zich goed te begrijpen is als we rekening houden met de enorme groei van ICT investeringen in de afgelopen jaren. De dubbele groeicijfers die voor ICT investeringen in statistieken worden gerapporteerd vinden we nu eenmaal niet voor de arbeidsinzet. De bijdrage aan de productiviteitsgroei van kapitaalverdieping blijkt nog groter te zijn als dezelfde vraag wordt onderzocht op microdata en gebruik wordt gemaakt van een econometrisch model. Econometrische schattingen laten een belangrijk hoger productiviteitseffect van investeren in ICT zien dan de uitkomsten van groeiboekhouding.

Hoewel de micro en de macro aanpak in kwalitatieve zin dus tot dezelfde conclusies komen blijft een belangrijke vraag onbeantwoord. De uitdaging ligt immers niet bij het vaststellen van de bijdrage aan de economische groei van ICT kapitaalverdieping maar bij de vraag wat ICT nu doet voor de TFP groei (de productiviteitsgroei die overblijft nadat de bijdragen van kapitaalverdieping aan de productiviteitsgroei zijn verdisconteerd). Het onderzoek in hoofdstuk 5 gaat in op deze vraag door de boekhoudkundige aanpak te confronteren met de econometrische aanpak op data voor bedrijven uit de commerciële dienstverlening (inclusief groot- en detailhandel). Kort samengevat komt de gevolgde werkwijze erop neer dat de econometrische specificatie wordt uitgebreid met variabelen die, enerzijds, niet in de groeiboekhouding voorkomen, maar, anderzijds, mogelijk wel relevant zijn voor het verklaren van verschillen in TFP groei tussen bedrijven.

De mogelijkheid dat aan ICT gerelateerde (externe) netwerkeffecten bijdragen aan de verklaring van verschillen in TFP groei is onderzocht door het opnemen van een 'ICT spillover' indicator in het econometrisch model. Deze variabele representeert de veranderingen in het ICT gebruik van de omgeving van een bedrijf. De achterliggende gedachte is dat eigen investeringen in ICT meer productiviteitswinsten genereren als andere bedrijven ook meer investeren in ICT middelen. Verder werd het model opnieuw doorgerekend voor bedrijven waarvan bekend was of zij al dan niet innovaties hadden doorgevoerd. Voor die bedrijven kon dus ook worden onderzocht of innoverende bedrijven een hogere TFP groei realiseerden dan niet-innoverende bedrijven als verschillen in (ICT) kapitaalverdieping zijn verdisconteerd.

Dit onderzoek bevestigt opnieuw dat innovatie belangrijk is voor TFP groei. Daarnaast toont het onderzoek aan dat 'ICT spillovers' een belangrijke verklaring geven voor de eerder genoemde verschillen in productiviteitseffecten van (ICT) kapitaalverdieping tussen de econometrische aanpak en de groeiboekhouding. Want als er rekening wordt gehouden met aan ICT gerelateerde externe effecten, dan leiden beide aanpakken tot nagenoeg dezelfde uitkomsten. Bovendien indiceert dit resultaat dat aan ICT gerelateerde (externe) netwerkeffecten een potentiële bron voor TFP groei zijn. De maatschappelijke baten van investeren in ICT kunnen dus aanzienlijk groter zijn dan het private rendement van individuele bedrijven.

Hoofdstuk 6 vergelijkt de bijdrage van ICT aan de productiviteitsgroei voor verschillende aggregatieniveaus van de data (macro en micro) en vult de analyse van hoofdstuk 5 aan door te kijken naar wat de wisselwerking tussen ICT en innovatie doet voor de productiviteitsgroei van bedrijven. Dat laatste is een lastig onderwerp omdat het niet eenvoudig is om te 'meten' hoe bedrijven ICT middelen gebruiken. In essentie geven data over ICT investeringen op dit punt immers weinig tot geen informatie, en dat terwijl ICT nu juist een technologie is die voor veel doelen kan worden ingezet.

Zoals aan het begin van deze samenvatting is uitgelegd, is ICT niet alleen een vorm van in computers belichaamde innovatie maar ook een zogenaamde 'enabler' van innovatie.

Investeringen in ICT middelen kunnen dus onderdeel zijn van een breder innovatieproces, bijvoorbeeld een proces dat mikt op het verbeteren van de informatiestromen binnen een bedrijf. Om die reden mag worden aangenomen dat ICT investeringen gepaard kunnen gaan met – of juist voortkomen uit – organisatorische veranderingen. Hiermede betreden we het terrein van de zogenaamde 'niet-technologische' innovaties. Ook hier geldt dat 'meting' verre van eenvoudig is. Desondanks is wel bekend of bedrijven niet-technologische innovaties hebben doorgevoerd (o.a. gemeten in de CIS). Die informatie is gebruikt om te onderzoeken of de combinatie van meer investeren in ICT en het doorvoeren van niet-technologische innovaties additionele productiviteitswinsten genereert en of deze winsten groter zijn dan bij technologische innovaties in de vorm van productvernieuwing.

De uitkomsten indiceren dat ook 'niet-technologisch' innoveren leidt tot een hogere TFP groei. Verschillen tussen beide vormen van innoveren treden pas op als we kijken naar de persistentie van innoveren. Dan blijkt dat voor bedrijven die in opeenvolgende jaren productvernieuwing toepassen een belangrijk hogere TFP groei is gemeten dan voor meer incidenteel innoverende bedrijven, een uitkomst welke correspondeert met het Schumpeter II model van cumulatieve kennisaccumulatie. Anderzijds, maakt het bij 'niet-technologische innovaties' blijkbaar niet uit of deze continue of slechts af en toe plaatsvinden. Samen suggereren deze uitkomsten dat productinnovatie uiteindelijk toch de belangrijkste determinant van de productiviteitsgroei is.

Het laatste hoofdstuk richt zich niet op innovatie maar is desondanks niet minder interessant omdat het ingaat op een actueel onderwerp met belangrijke beleidsimplicaties. Het hoofdstuk bespreekt onderzoek rond twee aan elkaar gerelateerde vragen: 1) in welke mate zijn er schaalvoordelen te behalen bij de productie van diensten en 2) zijn institutionele factoren in de vorm van marktregulering en toetredingsbarrières een belemmering voor het doorgroeien van bedrijven en dus ook voor het behalen van schaalvoordelen? De aanleiding tot deze probleemstelling is dat de relatief lage productiviteit(sgroei) in de dienstensector bij een toenemende afhankelijkheid van die sector een potentiële bedreiging vormt voor de productiviteitsontwikkeling in andere bedrijfstakken en dus ook voor de macroproductiviteitsgroei.

Om die probleemstelling te kunnen onderzoeken is er gebruik gemaakt van internationale bedrijfsgegevens. De internationale dimensie in de data maakt het mogelijk om te kijken naar de rol van verschillen in marktregulering en toetredingsbarrières tussen landen. Voorbeelden zijn verschillen in de kosten die gemaakt moeten worden voor het opstarten van een bedrijf, onduidelijke en overbodige regelgeving ten aanzien van toelatingseisen voor vestiging op buitenlandse markten of zelfs expliciete handels- en investeringsbeperkingen. Hoewel bepaalde structuurkenmerken (veel kleine bedrijven die opereren op lokale markten) anders doen vermoeden wordt marktwerking ook voor de zakelijke dienstverlening naar verwachting in de toekomst steeds belangrijker. Die trend hangt samen met technologische ontwikkelingen waardoor steeds meer vormen van dienstverlening zich lenen voor uitbesteding aan buitenlandse bedrijven. Een voorbeeld is de toenemende uitbesteding van ICT gerelateerde diensten naar India.

De belangrijkste conclusie van dit onderzoek is dat er in de zakelijke diensten aanzienlijke schaalvoordelen zijn te behalen. De uitkomsten indiceren dat bedrijven met 20 of minder werknemers een duidelijk lagere productiviteit kennen dan grotere bedrijven en dat de via econometrische methoden bepaalde technische efficiëntie het laagst is voor de kleinste bedrijven. De lage technische efficiëntie van de kleinste bedrijven blijkt o.a. verband te houden met toetredingsbarrières. Het onderzoek laat zien dat hogere toetredingskosten een belemmering vormen voor de toetreding van nieuwe bedrijven, waardoor kleine bedrijven minder geprikkeld worden om meer efficiënt te werken.

George van Leeuwen

Curriculum Vitae

George van Leeuwen was born in Alphen aan den Rijn on 27 February 1950. After attending the secondary school in Alphen aan den Rijn and his military service he worked for some year as an accountant. During this time he completed his BA in economics, College of Education. In 1977 he started his civil career at the Ministry of Economic Affairs and in 1980 he received a bachelor degree at the Erasmus University of Rotterdam. On 1 December 1980 he started his career at Statistics Netherlands as a statistician at the Analysis Section of the Department of Manufacturing Statistics. On 1 August 1994 he joined the Statistical Methods Department of Statistics Netherlands as a researcher in different microdata projects. On 1 March 2002 he joined the Netherlands Bureau for Economic Policy Analysis (CPB), to work for the ICT and Productivity (ICA) project till 15 September 2003 when he returned to Statistical Methods Department of Statistics Netherlands. Since 1 February 2006 he is working as a senior researcher at the Science and Technology Section (belonging to the Division of Business Statistics) of Statistics Netherlands.