Technological Regimes, Schumpeterian Patterns of Innovation and Firm Level Productivity Growth

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Abstract

The paper investigates the relationships between technological regimes and firm-level productivity performance, and it explores how such a relationship differs in different Schumpeterian patterns of innovation. The analysis makes use of a rich dataset containing data on innovation and other economic characteristics of a large representative sample of Norwegian firms in manufacturing and service industries for the period 1998-2004. First, we decompose TFP growth into technical progress and efficiency changes by means of data envelopment analysis. We then estimate an empirical model that relates these two productivity components to the characteristics of technological regimes and a set of other firm-specific factors. The results indicate that: (1) TFP growth has mainly been achieved through technical progress, while technical efficiency has on average decreased; (2) the characteristics of technological regimes are important determinants of firm-level productivity growth, but their impacts on technical progress are different from the effects on efficiency change; (3) the estimated model works differently in the two Schumpeterian regimes. Technical progress has been more dynamic in Schumpeter Mark II industries, while efficiency change has been more important in Schumpeter Mark I markets.

Keywords: TFP growth; technical progress; technical efficiency; technological regimes; Schumpeterian patterns of innovation; CIS data

1. Introduction

The empirical literature studying the relationships between innovation and the productivity performance of firms represents by now a huge and important body of applied research. The field has recently experienced a surge of interest due to the increased availability of firm-level data for a large number of countries.

Some of these firm-level datasets, such as those from the *Community Innovation Survey* (CIS) in Europe, contain a rich variety of information on the innovative activities and strategies of thousands of enterprises, making it possible to significantly refine the measurement of inputs and outputs of the innovative process, as well as to include a variety of other related factors.

Recent microeconometric studies on the innovation-productivity link have increasingly made use of innovation survey data, and provided fresh empirical evidence on the relationships between innovation input and output, on the one hand, and between output and productivity, on the other (Crepon et al., 1998; Hall and Mairesse, 2006).

In our view, a crucial proposition that may be useful to refine this type of empirical approach is that the relationship between innovation and productivity may have a well distinct nature in different types of markets and industrial sectors. In order to refine our understanding of the innovation-productivity link, we need a theoretical approach that takes into account the sector-specific nature of technological change (Dosi, 1988; Malerba, 2002; Laursen and Meliciani, 2002).

The general idea we put forward is that, since firms in different industries of the economy face a distinct set of opportunities, constraints and conditions, these industry-specific characteristics play an important role to explain the enterprises' technological and productivity performance. In particular, in line with the recent work of Castellacci (2007), we argue that firm-level productivity growth is related to the characteristics that define the technological regime in which the enterprise operates (Malerba and Montobbio, 2003; Park and Lee, 2006).

More specifically, we explore the idea that the sources and mechanisms of productivity growth may be distinct in different types of sectoral market structure and industrial dynamics conditions (Foster et al., 1998; Santarelli and Vivarelli, 2007). In a Schumpeter Mark II regime, the oligopolistic and concentrated nature of the market may make large incumbent innovators the dominant carriers of productivity growth. In contrast, the dynamics of productivity in a Schumpeter Mark I pattern may be led by an intense and turbulent process of competition where new innovators are more productive than the exit firms they replace.

In exploring this main idea, it is crucial to distinguish and measure different sources of productivity growth. We make use of frontier production function methods (data envelopment analysis) to decompose the growth of total factor productivity (TFP) into two distinct components: *technical progress* and *technical efficiency* (Färe et al. 1994; Perelman, 1995; Zheng et al., 2003). The former is associated with changes in the best-practice production frontier, whereas the latter with other productivity changes, such as learning by doing, improved managerial practices, and change in the efficiency with which an existing technology is applied.

After having identified and measured these two distinct components of TFP growth, we will investigate (1) the role of technological regime-related factors to explain their dynamics, and (2) how the relationship between technological regimes, technical progress and efficiency change differs in the two Schumpeterian patterns of innovation.

The econometric study makes use of firm-level data for the Norwegian economy. The rich dataset we make use of combines together information from three different sources. Data for the estimation and decomposition of TFP are taken from a time series database that provides information on several thousands of Norwegian enterprises for the period 1998-2004. Data on innovative activities are from the *Third* and the *Fourth Community Innovation Survey* for Norway, referring to the 1998-2000 (CIS3) and 2002-2004 (CIS4) periods respectively. These three data sources all provide information on a very large sample of Norwegian enterprises in all manufacturing and service industries.

The paper follows this outline. Section 2 briefly reviews the empirical literature that provides the background and foundation for our study. Section 3 puts forward our theoretical model and main hypotheses. Section 4 presents the results of an econometric estimation of TFP growth, which identifies the separate contribution of technical progress and efficiency changes to the overall productivity dynamics of Norwegian firms. Section 5 shifts the focus to the determinants of these two components, and estimates an empirical model that tries to explain them by means of a set of variables measuring technological regimes and other firm-specific characteristics. Section 6 summarizes the results and concludes the paper.

2. The literature on innovation and firm-level productivity growth

In recent years, thanks to the increased availability and diffusion of large enterprise datasets, there has been a surge of interest in the measurement of productivity growth and the study of its determinants at the firm level (Caves, 1998; Foster et al., 1998; Bartelsman and Doms, 2000; Lotti, 2007; Santarelli and Vivarelli, 2007).

The measurement of firms' productivity has for a long time been an engaging field of applied research within industrial economics, which has produced a variety of models and techniques to estimate TFP and its dynamics (Heshmati, 2003). One interesting approach, in particular, has made use of frontier production function methods (e.g. data envelopment analysis) to decompose the growth of TFP into two distinct components, namely *technical progress* and *technical efficiency* (Nishimizu and Page, 1982; Färe et al. 1994).

Technical progress is associated with changes in the best-practice production frontier of an industry, i.e. changes that are led by the introduction of a technology that is new to a sector. By contrast, the growth of *technical efficiency* is related to improvements in the ability with which firms are able to make an efficient use of already existing techniques (i.e. previously introduced by other enterprises in the same industry), and may be associated to diverse sources of productivity change such as, e.g., learning by doing and improved managerial practices. The rationale and intuition of this method are discussed in further details in section 4 below.

Besides decomposing the dynamics of TFP, this empirical literature has investigated the determinants of these two distinct components, and tried to relate them to a variety of characteristics of the firms and of the institutional and market conditions in which they operate (e.g. Zheng et al., 1998; Zheng et al., 2003).

To the best of our knowledge, though, this type of firm-level studies has not yet analysed the relationships between the innovative activities and strategies of enterprises, on the one hand, and their performance in terms of technical progress and technical efficiency. Does innovation increase productivity by pushing the technological frontier further (technical progress), or by improving the efficiency with which existing techniques are applied (efficiency change), or both? And what type of innovative activities (strategies, expenditures) are more important to achieve increases in each of the two components? These interesting questions, still unexplored in the firm-level literature, motivate our study.

Perelman (1995) previously investigated these issues by focusing on the industry-level of analysis. His empirical analysis estimates TFP components for eight sectors and 11 OECD countries, and then studies the link between the productivity dynamics and some key explanatory factors among which the R&D intensity of each industry.[1] An interesting finding of this paper is that the R&D variable is shown to be positively related to the technical progress component of TFP and negatively related to the efficiency component. In the cross-country setting investigated by Perelman (1995), the interpretation of this finding is that industries that invest more actively in R&D activities are those that are closer to the world technology frontier and that continuously push it further. Our research questions and empirical approach are quite similar to Perelman's, but the important difference is that we shift the focus of the analysis to the firm-level and explicitly investigate – within each sector – the relationships between the innovative activities and strategies of enterprises, on the one hand, and the growth of their technical change and efficiency, on the other.

In approaching this research issue, the large empirical literature studying the relationship between innovation and productivity growth provides us with a set of important insights and well-established results, which are useful to give a more solid foundation to our study. Applied studies on the impact of R&D activities on the dynamics of productivity represent by now a huge and important body of empirical research. The standard approach is to investigate the empirical relationship between the growth of total factor productivity, on the one hand, and R&D expenditures and

[1] Besides R&D, the other explanatory factors included in Perelman (1995)'s regression model are the lagged efficiency level, the openness of the industry to international trade, the growth of investments in physical capital and the growth of GDP per capita.

R&D spillovers, on the other (Griliches, 1979; Los and Verspagen, 2004; Wieser, 2005).

Two recent developments in the innovation-productivity literature have particularly attracted the attention of scholars in the last few years. The first is the greater availability of innovation enterprise-level data for a large number of countries. Some of these firm-level datasets, such as those from the *Community Innovation Survey* (CIS) in Europe, contain a rich variety of information on the innovative activities and strategies of thousands of enterprises, making it possible to significantly refine the measurement of inputs and outputs of the innovative process and to include a variety of other related factors.

A second interesting development has been the progressive refinement of the traditional R&D productivity model. The current mainstream approach analyses innovation survey data by making use of the so-called CDM model (named after the authors of the seminal paper in this tradition, Crepon, Duguet and Mairesse, 1998). The CDM empirical model emphasizes the distinction between inputs and outputs of the innovative process, and points out that it is the innovative output that affects the productivity performance of firms, rather than their R&D activities (inputs) as commonly assumed by previous works.

This CDM type of studies typically estimates three equations: one for the determinants of innovation inputs (e.g. measured by total innovation intensity), one for the link between innovation input and output (measured by turnover from new products), and one for the impact of innovation output on productivity (labour productivity or TFP).

Besides the conceptual distinction between these different stages of the innovative process, another important contribution of this approach is the consideration of the possible problems created by the existence of sample selection bias in the context of firm-level data from innovation surveys. This problem typically arises because many of the questions on innovation strategies and activities in the CIS survey are only answered by firms that are innovative, whereas non-innovative enterprises skip those parts of the questionnaire that are not relevant for them. CDM econometric models control for and correct this type of selection-bias (e.g. by means of a generalized Tobit model, or the Heckman two-step procedure) and estimate an additional equation for the firms' propensity to innovate.

The results of these econometric studies are largely consistent with each other and provide fresh empirical evidence on the existence of a positive link between innovation input and output, on the one hand, and innovation output and productivity, on the other. These relationships have been found to hold in large CIS-based samples of firms in various European countries (Cainelli et al., 2006; Crespi et al., 2006; Duguet, 2006; Hall and Mairesse, 2006; Lööf and Heshmati, 2006; Parisi et al., 2006; Van Leuwen and Klomp, 2006). A few studies with availability of CIS data for more than one country have also presented comparative exercises (e.g. pooled regressions with data for different economies) that seem to indicate that the estimated relationship between input, output and productivity is quite similar across different countries in Europe (Lööf et al., 2001; Janz et al., 2003; Griffith et al., 2006).

Despite the merits of this recent approach, it is however also important to point out one possible limitation of it. From a theoretical point of view, this input-output-performance approach is rooted in a linear understanding of the innovative process that, despite its appeal and analytical power, does not provide a realistic conceptualisation of the relationships and complex feedback mechanisms between the innovative strategies of firms, their economic performance, and the sector-specific characteristics of the market in which they operate. Industry-specific factors, be they technological or economic, exert a considerable influence on the innovative strategies, opportunities and constrains faced by enterprises in different markets (Von Tunzelmann et al., 2008). The relationship between innovation and productivity, in our view, may have a well distinct nature in different types of markets and industrial sectors. In order to refine our understanding of the innovation-productivity link, we need a theoretical approach that takes into account the sector-specific nature of technological change.[2]

3. Theoretical model and main hypotheses

The model that we make use of is based on the notion of *technological regime*. A technological regime may be defined as the technological environment in which innovative activities take place in each sector of the economy (Nelson and Winter, 1982; Winter, 1984 and 2006). A set of industry-specific characteristics defines such a technological environment, providing opportunities and constraints for firms that seek to undertake innovative activities. These industry-specific features refer in particular to the following main characteristics (Cohen and Levin, 1989; Malerba and Orsenigo, 1995; Lee and Lim, 2001).[3]

[2] Another possible drawback of the CDM model approach refers more specifically to the empirical strategy that is commonly adopted to investigate the link between innovation and productivity. Despite the conceptual relevance of the distinction between innovation input and output, it is admittedly difficult to empirically estimate the relationship between them in the context of cross-sectional data such as those based on the CIS surveys. The lack of a reasonable time lag between input, output and productivity performance challenges the validity of this type of measurement exercises, which would arguably require a longer time span or a panel comprising different waves of the CIS survey. This type of refinements, based on the analysis of CIS panel data, is now possible thanks to the increasing availability of data from different waves of the innovation surveys, and it currently represents an important new avenue of research in the CDM model tradition.

[3] For a more extensive discussion of this approach and a comparison with the mainstream view, see Castellacci (2008a).

Cumulativeness conditions. These define the extent to which technological activities and performance build upon the accumulated stock of knowledge and technical competencies of each firm (Cefis and Orsenigo, 2001).

Level of technological opportunities. Technological opportunities are commonly defined as the likelihood that technological activities and expenditures lead to an innovative output, i.e. the pace and intensity of technological progress (Breschi et al., 2000). Innovative intensity is achieved, in addition to the internal R&D investments of a firm, also by the acquisition of external knowledge from other actors, e.g. expenditures for the acquisition of machinery, software and R&D services from specialized consultants.

External sources of opportunities. A complementary aspect is the ability of firms to recognize, imitate and exploit the pool of advanced knowledge that is available in the economic environment. External sources of opportunities may be used when firms are able to engage in interactions and cooperations with other agents in the innovation system, such as their suppliers, users, competitors, private R&D labs, Universities and other public research institutes (Laursen and Meliciani, 2002; Reichstein and Salter, 2006).

Appropriability conditions. Firms typically make use of a variety of instruments to protect the results of their innovative activities from imitation (Dosi et al., 2006). Appropriability means can roughly be distinguished into formal (e.g. patents and trademarks) and informal means (e.g. process secrecy and know-how, and the complexity of the product and related design).

In a nutshell, the main insight of this approach is that the innovative strategies and activities of enterprises greatly vary across sectors because industries differ fundamentally in terms of the properties of their technological regimes (Malerba and Montobbio, 2003; Park and Lee, 2006). Our theoretical approach is rooted in this recent line of research, and tries to bring it one step further.

The general idea we put forward is that, since firms in different sectors of the economy face a distinct set of opportunities, constraints and conditions, these industry-specific characteristics play an important role to explain the enterprises' technological and productivity performance.

In particular, in line with the recent work of Castellacci (2007), we argue that the growth of productivity of a firm is related to the characteristics that define the technological regime in which the enterprise operates. More specifically, we may expect the productivity performance of an enterprise to be related to the cumulativeness of its innovative process, its level of technological opportunity, its ability to exploit external sources of opportunity, and the effectiveness of its appropriability strategy.

Hypothesis 1. The characteristics of technological regimes are important determinants of the productivity growth of firms.

This general hypothesis may be sharpened and refined by looking at two interrelated and more specific aspects. The first is the distinction between the two distinct sources of productivity growth pointed out in the previous section, i.e. technical progress and efficiency changes. It would be reasonable to think that the characteristics of technological regimes may have different impacts on these two components of TFP growth.

In particular, since the *technical progress* component measures upper shifts in the technological frontier due to the introduction of techniques that were not previously available in an industry, we may expect it to be related to the degree of cumulativeness of technological change and to the level of technological opportunities (both aspects reflecting firms' commitment to, and intensity of, internal R&D activities; see also Perelman, 1995). By contrast, the *efficiency change* component, which accounts for improvements in the ability with which firms are able to make an efficient use of already existing technologies, may arguably be related to firms' efforts to exploit external sources of knowledge (e.g. R&D purchase, consultancy services, etc.) rather than to their capability to internally create radically new technologies. In short, we put forward the following

Hypothesis 2. The impacts of technological regime-related factors on technical progress are different from the effects on efficiency change.

A second aspect that it is important to look at in order to sharpen our theory is the type of market structure and industrial dynamics that characterize each industry. The empirical literature on technological regimes has previously investigated the relationships between technological regimes and the characteristics of market structure and industrial dynamics in different sectors of the economy. Several recent works in this field have in particular focused on differences in terms of concentration of innovative activity, size of innovative firms, ease of entry in the market, turbulence or stability in the population of innovative firms (Malerba and Orsenigo, 1995 and 1996; Breschi et al., 2000; Van Dijk, 2000).

These studies have shown that the properties of technological regimes may explain the existence of the innovation patterns originally pointed out by Schumpeter (1934 and 1943). The first, the *Schumpeter Mark I*, is characterized by high ease of entry in the market, low concentration of innovative activity, and a turbulent population of new and old innovators with a significant role played by small firms. Creative destruction (Schumpeter, 1934) is the main feature of this regime (also defined 'entrepreneurial' or 'widening'). The second, the *Schumpeter Mark II* pattern, is characterized by high barriers to entry for new innovators, high concentration of innovative activity, and a stable population mainly formed by large and well-established firms. Creative accumulation (Schumpeter, 1943) is the distinctive feature of such a regime, also defined 'routinized' or 'deepening'.

The stylised distinction between Schumpeter Mark I and II and its relationship to the properties of technological regimes suggest a further refinement of our framework. It is reasonable to conceive, we argue, that the relationship between technological regime-related factors and productivity growth that our model explores will be different in the two Schumpeterian patterns of innovation. The reason is that the mechanism that links innovative activities, technical progress and efficiency changes may indeed work differently in distinct types of market structures.

In the Schumpeter Mark II regime, high cumulativeness and appropriability conditions create strong technological entry barriers for new innovators. Productivity growth in this type of market may be assumed to be, to a large extent, the result of a continuous process of knowledge accumulation by well-established oligopolistic innovators, where the key sources of growth are thus represented by dynamic economies of scale and the persistence and cumulativeness of innovative activities. Incumbents continuously push the technological frontier further, so that, on average, it is technical progress that represents the dominant source of productivity dynamics for the industry.

In a Schumpeter Mark I pattern, on the other hand, low cumulativeness and appropriability conditions tend to facilitate the continuous entry of new innovative firms. In this context, productivity growth is more likely to be related to the process of creative destruction that continuously characterizes a turbulent market, where new innovators are more productive than the exit firms they replace. In a highly competitive market, the ability of firms to make efficient use of rapidly changing production techniques becomes a crucial factor. For this type of industry, therefore, efficiency improvements may be expected to constitute a more relevant mechanism of productivity growth.

Hypothesis 3. The relationship between technological regimes, technical progress and efficiency changes works differently in different Schumpeterian patterns of innovation. In particular:

- **Hypothesis 3a**. Technical progress is greater in the Schumpeter Mark II than in the Schumpeter Mark I pattern.

- **Hypothesis 3b**. Efficiency change is greater in the Schumpeter Mark I than in the Schumpeter Mark II pattern.[4]

[4] Hypothesis 3 may also be expressed with reference to the idea and terminology recently put forward by Aghion et al. (2005) in their study of the inverted U relationship between competition and innovation. This seminal paper points out that in competitive neck-and-neck markets (roughly corresponding to a Schumpeter Mark I regime) firms must continuously implement advanced

4. A decomposition of TFP growth

The first part of our empirical investigation focuses on total factor productivity and decomposes its growth by means of data envelopment analysis. The results of this decomposition exercise will then be used in the next section as dependent variable in a regression analysis that studies the link between innovation and productivity performance.

We make use of frontier production function methods to study the dynamics of productivity of Norwegian firms. This first part of the analysis is based on the *Tidsseriebase* dataset, containing information on value added, labour and capital investments (deflated by means of industry-level indexes) for a large sample of Norwegian enterprises in all manufacturing and service industries for the period 1998-2004. The number of observations in the dataset varies between around 4000 and 6000 firms for each of the years in the time span.

The Malmquist Index model is based on the non-parametric deterministic production frontiers estimated via data envelopment analysis (DEA; Färe et al. 1994). This approach allows decomposing the dynamics of TFP into technical progress and technical efficiency change. The former is associated with changes in the best-practice production frontier, and the latter with other productivity changes, such as learning by doing, improved managerial practices, and change in the efficiency with which an existing technology is applied.

technologies in order to maintain their competitive position (the "escape competition effect"). By contrast, in less competitive industries (Schumpeter Mark II) incumbent firms dominate the technology market (the traditional "Schumpeter effect"). Our third hypothesis argues that these different types of market structure lead to well-distinct mechanisms of productivity growth, where efficiency change prevails in the former and technical progress in the latter case.

The main intuition of the method is the following.[5] For each industry, the DEA methodology follows the following steps: (1) it identifies the best-practice firms, i.e. the enterprises that have the highest output (value added) for any given level of input (capital and labour); these best-practice firms define the empirical production frontier of the industry (in year *t*); (2) the DEA then calculates the level of technical efficiency for all firms in the industry, which is also a measure of how distant an enterprise is from the best-practice frontier of its sector (i.e. a measure of the technology-gap); (3) by comparing the production frontier and the technical efficiency levels of each firm between year *t* and *t+1*, it is then possible to calculate the growth rate of technical progress (i.e. shifts in the empirical production frontier) and the growth rate of technical efficiency (i.e. the extent to which a firm has got closer to the frontier over time). The overall growth rate of TFP (Malmquist index) is defined as the geometric average of these two components.

The DEA represents a useful method to decompose the dynamics of total factor productivity. In the context of the analysis of innovation and technological change, this empirical methodology may be particularly interesting for the following reasons. First, at the firm-level, it provides a measure of the extent to which each enterprise has been able to introduce technologies that are new to its market (thus pushing the technological frontier further) and/or making a more efficient use of techniques already available in the industry (i.e. previously introduced by other firms). Secondly, at the industry-level, aggregating this type of firm dynamics gives an interesting indication of the overall productivity trajectory of each sector, i.e. whether it has been characterized, on average, by shifts in the technological frontier or rather by a process

[5] A formal presentation of the method is reported in the Appendix. See also Färe et al. (1994) and Färe and Grosskopf (1996).

of catching up where many enterprises have improved their technical efficiency over time.

Thirdly, from a theoretical point of view, the DEA method is rather eclectic and flexible, since it does not impose any strong *a-priori* assumptions on the data. In fact, DEA is a non-parametric method that does not assume any specific functional form for the production function. Quite on the contrary, by distinguishing the most productive from the less efficient firms, the technique *lets the data speak*, and it explicitly recognizes *firm heterogeneity* as a major characterizing feature of each industry. Thus, while the distinction between shifts in the production frontier (technical progress) *versus* movements towards the frontier (efficiency change) was originally rooted in a mainstream production function approach, its application within a non-parametric DEA context is actually quite consistent with an evolutionary economic environment where heterogeneous firms continuously compete by trying to imitate existing technologies and by introducing new ones.[6] Besides these three advantages of the method, there are also some possible drawbacks. We discuss these econometric issues in the Appendix.

We have applied this productivity decomposition method to our large sample of Norwegian enterprises in all manufacturing and service industries for the period 1998-2004. First we have run the DEA for each industry (defined at the 3-digit level) and

[6] One important caveat has to be made regarding the heterogeneity issue pointed out here. The DEA methodology typically distinguishes the best-practice firms from the less efficient units based on the combination of input (e.g. capital and labour) and output that they use in any given period. In a second step, it is then possible to examine the factors that may explain the heterogeneity of firms' productivities (this is what we do in the second part of our empirical analysis, see section 5). However, a different approach to the analysis of firms' heterogeneity does instead argue that it is indeed conceptually difficult to define and identify best-practice firms *within each industry*, because enterprises belonging to each sector are characterized by a great variety of innovative strategies, patterns and performance. In other words, the factors explaining firm heterogeneity are not limited to industry-specific variables, since there could also be common patterns among enterprises that belong to different sectors (Srholec and Verspagen, 2008). In this alternative approach, the analysis and exploration of the heterogeneity of innovation across firms (and sectors) should be the natural first step of the analysis (e.g. by means of factor and cluster analysis), which could then be followed in a second stage by the analysis of the link between each pattern identified at the firm-level and the performance of enterprises.

each year; then, we have calculated the annual growth rates of TFP and of its two components. Table 1 reports the results of these estimations for the two sub-periods 1998-2001 and 2002-2004, i.e. the dynamics of TFP, and its decomposition into the technical progress and the efficiency change components. The various rows of the table present averages by sector of firm-level productivity growth.[7] For interpreting these results, it should be noticed that values greater (lower) than 1 indicate positive (negative) growth of TFP (and of its two components).

< Table 1 here >

Looking at the Malmquist TFP index, the table indicates that the growth of total factor productivity has been positive for most of the sectors. The country average is significantly higher in the second period (10.16%) than in the first one (around 4.36%). The sectors that have experienced the most rapid pace of TFP growth are quite diverse, and belong to both manufacturing and services and to both high- and medium-low-tech branches of the economy: food and beverages, leather and footwear, basic metals, motor vehicles, other transport equipment, recycling, radio and TV, wholesale trade, air transport and telecommunication. This would suggest that the process of technological transformation has not only played a relevant role for the most technologically advanced branches of the economy, but also for some of the mature sectors that have traditionally constituted a stronghold of the Norwegian industrial system (Von Tunzelmann and Acha, 2005).

[7] The table reports the average TFP growth for each industry at the *2-digit level* in order to save some space, although, as specified above, our DEA estimations have been carried out for each *3-digit level* sector. Our dataset does not enable to focus on a finer disaggregation level than the 3-digit, since for many of the industries in our sample the number of observations would be not sufficient to run the DEA if we defined the sector at, e.g. the 4- or 5-digit level.

Shifting the focus to the two components of TFP growth, the table suggests that the dynamic pattern of productivity has mostly been obtained, in both sub-periods, by means of technical progress rather than through improvements in technical efficiency. On average, the technical progress component has grown by nearly 18% in the first and 26% in the second period. The growth rate has been particularly high for industries such as electrical, radio and TV, furniture, recycling, sea transport, telecommunication, and computing and software. These are industries that have experienced a high pace of technical progress accompanied by a significant decrease (negative growth) of the efficiency change component.[8]

Technical efficiency has on average decreased by nearly 8% in the first period and 7% in the second. Different sectors have however contributed quite differently to the negative average performance of the efficiency change component, and some industries have indeed experienced efficiency increases in at least one of the two sub-periods (e.g. mining and quarrying, food and beverages, textiles, leather and footwear, basic metals, electrical, motor vehicles, other transport equipment, wholesale trade, air transport, telecommunication).

Summing up, our decomposition exercise indicates that in the period 1998-2004: (1) TFP growth has mostly been obtained through technical progress, whereas technical efficiency has on average decreased; (2) behind this aggregate pattern, the performance of different sectors (and of firms in different industries) has been quite diverse. What are the factors that may explain the diverging dynamics followed by technical progress and efficiency, and to what extent can this be accounted for by the

[8] This is not surprising in the context of our DEA estimations. In fact, if an industry experiences a rapid pace of technical progress, it is reasonable to think that many enterprises below the frontier will face an enlargement of the technology-gap *vis-vis* the frontier firms. In other words, the catching up process of follower firms will be more difficult if the technological frontier of the industry is shifting rapidly over time.

characteristics of technological regimes and the related patterns of market structure and industrial dynamics that characterize different sectors?

5. The link between innovation, technical progress and efficiency

In order to answer this question, the second part of our empirical analysis makes use of innovation data and merges them with the TFP data discussed in the previous section. Data on innovative activities are from the *Third* and the *Fourth Community Innovation Survey* for Norway, referring to the 1998-2000 (CIS3) and 2002-2004 (CIS4) periods respectively. CIS data provide information on a large and representative sample of Norwegian enterprises in all manufacturing and service industries. By merging the CIS3, CIS4 and the TFP data previously estimated from the *Tidsseriebase* dataset, we are left with a two-period cross-sectional sample, containing around 1000 firms in the first (CIS3) and 1650 firms in the second period (CIS4).

5.1 CIS data, indicators and descriptive analysis

We make use of the following indicators, all of which are available in both periods and have identical definition in the two waves of the innovation survey.

Firm-specific factors

- **Employment (log):** Number of employees (log), a standard measure of firm size.

- **Group**: a dummy variable indicating whether a firm belongs to a group.

- **Product life**: a variable indicating the average length of the firm's product cycle.

- **Export intensity:** export divided by total turnover, in 2001 and 2004.

- **Market location:** a categorical variable that indicates whether a firm sells its products and services in local, national, European or other international markets.

- **TFP level:** level of total factor productivity, average of the period.

Technological regimes factors

- **Cumulativeness:** Continuous R&D: a dummy variable that indicates whether a firm is *continuously* engaged in R&D activities (rather than being an occasional innovator).

- **Level of technological opportunities**: We make use of three indicators to measure the intensity of a firm internal R&D effort as well as its acquisition of external R&D and other types of specialized knowledge. (1) R&D intensity (internal R&D expenditures, share of total turnover); (2) Other external knowledge (acquisition of software and other external knowledge, share of total innovation costs); (3) R&D purchase (expenditures for the purchase of R&D, share of total innovation costs).

- **External sources of opportunities**: a set of dummy variables indicating whether a firm regards the following actors as important sources of information for their technological activities: other sources in the same firm (S-Internal); other firms in the same group (S-Group); suppliers; users; competitors; consultants; private R&D labs; Universities; public research institutes.

- **Appropriability conditions:** Two dummy variables that indicate whether each firm has made use of the following (formal and informal) appropriability modes: trademark; patent; secrecy; complex design.

Other innovation-related variables

- **Effects of innovation:** Three dummy variables indicating whether each firm states that technological change has led to the following effects and results: increasing market shares or entering new markets (E-Market orientation); increasing the productive capacity (E-Productive capacity); decreasing the labour costs (E-Labour costs).

- **Hampering factors:** A set of dummy variables indicating whether a firm considers the following factors as important obstacles to its innovative activities: high costs (H-Costs); lack of qualified personnel (H-Personnel); lack of information on technology (H-TechInfo); lack of other information (H-OtherInfo).

Table 2 presents some descriptive evidence on the variables measuring firm-specific factors. The table reports the mean and standard deviation of these variables for both the CIS3 and the CIS4 dataset. As customary in this type of analysis based on CIS data, the table reports these descriptive statistics separately for the innovative and non-innovative sample (the distinction is applied by means of an "innovator dummy" variable that takes value 0 if a firm has had no innovation costs at all, and 1 otherwise).

The differences between the innovative and non-innovative samples are evident in both periods, and their statistical significance is shown through the results of a non-parametric Mann-Whitney U test. In particular, firms in the innovative sample are characterized by higher TFP levels, greater firm size and group structure, shorter product life cycle, higher export intensity and greater relevance of international commercialisation markets.

This descriptive evidence, which is consistent with what previous studies based on CIS firm-level data have found for other countries, provides one first relevant indication for the econometric study that we intend to undertake. Given the significant differences between innovative and non-innovative firms in our sample, selection-bias may occur in our econometric estimations. This is due to the fact that in the CIS questionnaire non-innovative enterprises do not answer the questions on innovative activities, strategies and performance, and are therefore excluded from the regressions studying the links between innovation and productivity growth. For this reason, in order to take into account this type of sample selection problem, the estimations that we will present make use of a Heckman two-step procedure, as standard in the CDM econometric approach (see section 2).

< Table 2 here >

Next, we present some descriptive evidence on the differences between the characteristics of firms in distinct Schumpeterian regimes. Table 3 reports the mean and the coefficient of variation (CV) of firms in the two distinct types of market structure and industrial dynamics that are typically labelled Schumpeter Mark I and Schumpeter Mark II.

The distinction between Schumpeter Mark I and II regimes, while clear from a conceptual point of view, is not easy to apply in empirical analyses, since there exist no well-established criteria to decide whether each sector of the standard industrial classification belongs to one or the other regime. Previous empirical studies in the field, however, have carefully analysed this aspect and provided a list of industries belonging to each Schumpeterian regime (Malerba and Orsenigo, 1995, p. 58; Breschi et al., 2000, p. 400; Van Dijk, 2000, pp. 192-194; Marsili and Verspagen, 2002, pp. 814-815; Castellacci, 2008b). In addition, the recent paper by Castellacci et al. (2009) has investigated this issue by means of a factor and cluster analysis exercise applied to a large number of indicators on market structure and industrial dynamics of Norwegian firms in all manufacturing and service industries. Our division of sectors into Schumpeter Mark I and II regimes follows therefore these previous empirical works.[9]

For both periods, table 3 reports the results of a non-parametric Mann-Whitney U test that investigates the differences between firms in the two Schumpeterian regimes. The test confirms that enterprises differ significantly when they operate in distinct market and industrial dynamics conditions. Firms in the Schumpeter Mark II pattern have on

[9] The list of sectors in the two Schumpeterian regimes is the following. *Schumpeter Mark I sectors*: mining; textiles; wearing; leather and footwear; wood and related products; printing and publishing; non-metallic mineral products; fabricated metals; machinery and equipment; electrical; radio and TV; medical and optical; other transport equipment; furniture; recycling; construction; wholesale trade; land transport; auxiliary transport services; research and development. *Schumpeter Mark II industries*: motor vehicles; food and beverages; pulp and paper; basic metals; sea transport; air transport; telecommunication; computing and software; other business services.

average higher R&D intensity and greater cumulativeness of technological change, and they also tend to be larger and more oriented to international markets.

While this confirms the basic characteristics of the Schumpeter Mark I and II distinction, a more novel indication is provided by the analysis of their differences with respect to the variables measuring productivity dynamics. The technical progress component of TFP growth proves to be significantly more dynamic for firms in the Schumpeter Mark II regime, whereas the efficiency change component is higher for enterprises in the Schumpeter Mark I type of markets. Considering the joint effects of these two components of productivity, the growth of TFP has been slightly larger for firms in the Schumpeter Mark I than in the Schumpeter Mark II pattern (3.5% against 0.7%, and 6.4% versus 3.9%).

This finding is, in our view, quite interesting, and it provides empirical support for the third hypothesis that we have previously put forward (see section 3, hypotheses 3a and 3b). Our interpretation of this result is that the mechanism of productivity growth differs in the two Schumpeterian regimes. While Schumpeter Mark II markets are characterized by an oligopolistic structure where large incumbent innovators continuously and cumulatively push the technological frontier further (technical progress), firms in Schumpeter Mark I industries must devote a significant effort to make an efficient use of already available techniques (efficiency change), which is a crucial requirement to survive in competitive and turbulent markets.

< Table 3 here >

5.2 Model specification and estimation results

In the analysis of the links between innovation and productivity growth, we employ a model specification and estimation strategy able to take into account the two issues highlighted by the descriptive evidence presented in section 5.1. The first, the possible problem of selection-bias, is tackled by making use of the Heckman two-step methodology. The second, the differences between firms in the Schumpeter Mark I and Mark II patterns, is taken into account by estimating a piecewise linear regression version of the model (i.e. by including constant and slope dummies to control for differences among the two regimes).

The Heckman two-step estimation method corrects for the possible presence of selection-bias that is caused by the exclusion of non-innovative firms (which, as previously shown, are significantly different from enterprises in the innovative sample). In line with the CDM model approach (see section 2), the first step of the procedure estimates a selection equation, which investigates the factors explaining the probability that a firm is an innovator. The second step studies the links between innovation and productivity growth, including, among the other regressors, also the inverse Mills ratio that corrects for the sample selection bias.

The dependent variable in the selection equation is an "innovator dummy" variable (taking value 0 if a firm has had no innovation costs at all, and 1 otherwise). The explanatory factors are firm-specific indicators that are typically used in recent CDM applied works (Hall and Mairesse, 2006). Nearly all of these factors turn out to be significant in the first-step regression presented in the tables. The probability of being an innovator increases with firm size, its group structure, its international market orientation, and it decreases with the length of the product life (suggesting that the shorter the life cycle the greater the need to invest in innovative activities). Besides, the probability of being an innovator is positively related to the four dummy variables measuring different types of hampering factors in the innovative process, i.e. high costs, lack of qualified personnel, lack of technical information or other types of information. The positive sign of this estimated relationship is not surprising and it is consistent with previous works, suggesting that innovative firms have a greater awareness of the main factors that hamper their innovative activities.

The second-step equation studies the relationships between innovation and the two distinct components of TFP growth. We therefore estimate two distinct (second-step) equations. The first relates the growth of technical progress to the set of explanatory variables that have been presented in section 5.1, namely the characteristics of technological regimes and a set of other firm-specific factors. The second equation makes use of the same set of explanatory variables to explore their impact on the growth of efficiency.

Our choice of including the same set of explanatory variables in the two (second-step) equations may be justified on the following grounds. In principle, there is no reason to assume that the same factors will explain equally well both technical progress and efficiency change, and our hypothesis 2 does in fact argue that we should expect the technological regimes variables to have distinct effects on the two components of productivity growth. However, there exists no clear prior knowledge, i.e. previous analytical models or empirical results, indicating what type of innovative activities (strategies, expenditures) may be more important to explain one productivity component or the other. Therefore, in an exploratory fashion, we include the same set of explanatory variables in the two equations in order to see whether there is any important difference in the working of the technological regime model for the two distinct types of productivity changes.

For each of these two equations, we estimate three different specifications: the first includes dummies for all manufacturing and service industries; the second includes, instead of the whole set of industry dummies, a constant dummy for firms in Schumpeter Mark II sectors; the third specification includes, in addition, a set of slope dummies for enterprises in Schumpeter Mark II sectors.[10] All the regressions also include a time dummy that controls for differences between the two sub-periods. Results for the determinants of technical progress are presented in table 4, whereas those for efficiency change are reported in table 5.

Table 4 provides basic support for our technological regime model, and indicates that the statistical precision of many of the estimated coefficients is higher in the versions of the model that control for differences between the two Schumpeterian patterns of innovation (reported in the last two columns). Among the firm-specific factors, technical progress is positively related to firm size, the 'part of a group' dummy variable (in the Schumpeter Mark II), and the international location of markets (only in the Schumpeter Mark I). It is instead negatively related to the length of the product life, which has a much stronger effect in the Schumpeter Mark II than in the Mark I pattern.

Besides, the level of TFP turns out to have a high negative estimated coefficient, and this inverse relationship between TFP level and technical progress appears to be even more pronounced in the Schumpeter Mark II regime. A possible interpretation of this finding may point to the existence of a (short-run) trade-off between the efforts and

[10] In the piecewise linear regression version of the model, slope dummies have initially been included for all of the explanatory variables. However, in the final specification presented here the slope dummies have been retained only if their inclusion contributes to improve the explanatory power of the model. When a slope dummy is included in the regression, the estimated coefficient for the Schumpeter Mark II regime is the algebraic sum of the overall estimated coefficient of the regressor and the one of the corresponding slope dummy. On the other hand, if the slope dummy is not included, the estimated coefficient is the same for the two regimes.

investments that are necessary for searching for radically new technologies, on the one hand, and the achievement of technical efficiency, on the other. Enterprises that devote substantial efforts to the introduction of technical progress may find it harder to achieve a full exploitation of other advanced techniques already available in the market (e.g. because they focus on internal rather than external opportunity sources). Relatedly, the negative estimated relationship between TFP level and technical progress does also indicate that it is not always the same best-practice firms that introduce new technologies; enterprises below the frontier do also manage to catch up and shift the industry frontier over time (Aghion et al., 2005). This is more clearly the case in the Schumpeter Mark II regime, our results indicate, since this is a type of markets where oligopolistic innovators (be they best-practice or below the frontier) compete with each other by continuously introducing new technologies.

Shifting the focus to the technological regime explanatory variables, we observe that the coefficient of the cumulativeness dummy variable is positive, as expected, but when we control for differences between the Schumpeter Mark I and II, it turns out to be negative for the latter. Regarding the variables measuring the levels of technological opportunity, the R&D intensity turns out to be positive, and the variable measuring the acquisition of software and other external knowledge has a quite strong positive effect on technical progress.[11] Among the external sources of opportunity dummy variables, only internal sources and competitors on the same market have a significant estimated coefficient (in at least some of the regressions). The dummies measuring formal and informal appropriability means are instead not significant at conventional levels.

[11] The finding of a positive relationship between R&D intensity and technical progress is in line with the industry-level study carried out by Perelman (1995).

The last group of regressors measure other aspects of the innovative process, such as hampering factors and effects of innovation. These variables provide some additional interesting indications on the nature and performance of innovative activities of Norwegian firms. The lack of qualified personnel is negatively related to productivity growth, while the lack of technical information is negatively (positively) related to it in the Schumpeter Mark II (Mark I) regime. On the other hand, the variables measuring the firm ability to increase market shares and entering new markets and the expansion of its productive capacity have both a positive effect on technical progress.
Last, the time dummy confirms that technical progress has been stronger in the second than in the first period (see section 4, table 1), while the Schumpeter Mark II constant dummy indicates that technical progress has been significantly more rapid for firms in the Schumpeter Mark II than in the Schumpeter Mark I. This provides further empirical support for the third hypothesis put forward in section 3 (see hypothesis 3a).

< Table 4 here >

Table 5 presents the results of the estimations exploring the determinants of the efficiency change component of TFP growth. First, looking at the set of firm-specific indicators, efficiency improvements are positively related to firm size, the 'part of a group' dummy variable, and the international market orientation of the enterprise. These results are in line with previous studies exploring the determinants of efficiency change at the enterprise level (Zheng et al., 2003).
The main difference as compared to the results in table 4 refers to the TFP level variable. This turns out to be positively related to the dynamics of technical efficiency. One possible interpretation of this finding is that the dynamics of technical

efficiency, representing mechanisms such as learning by doing, improvements in managerial practices and the acquisition of external knowledge, grows in a cumulative way because it builds upon existing levels of knowledge stocks, human capital and the absorptive capacity of a firm. In other words, this result indicates that firms that are characterized by higher efficiency levels are also better able, over time, to implement advanced techniques that are available in the industry (i.e. previously introduced by other innovating firms), whereas enterprises that are too distant from the frontier are less successful in this respect. Table 5 also suggests that this type of cumulative catching up mechanism within each industry is stronger in the Schumpeter Mark II regime, because this type of market is characterized by a greater polarization between best-practice *versus* distant-from-frontier firms: the former (oligopolistic producers that dominate the market) continuously improve their technical efficiency, while the latter are not able to keep up with the rapidly moving technological frontier.

Secondly, some of the effects of the technological regime related variables do also differ. The purchase of R&D from external specialized providers seems to be an important channel to improve technical efficiency, whereas the internal R&D and cumulativeness variables are not significant in the two model specifications that control for differences between the Schumpeterian regimes. Among the external sources of opportunities, internal sources and consultants turn out to be relevant channels to achieve efficiency improvements.

Thirdly, the group of variables measuring other aspects of the innovative process also shows some interesting differences *vis-à-vis* the determinants of technical progress. The hampering factors indicators are in fact both positively related to efficiency change, a possible interpretation being that when there exist significant obstacles to undertake innovative activities, a more convenient strategy for the firm is instead to devote resources to the improvements of its technical efficiency. As for the variables measuring the effects of innovation, efficiency growth is positively related to the market orientation of the firm and to its ability to save on labour costs. It is also negatively linked to increases in the firm's production capacity, since a higher productive capacity makes it more difficult for an enterprise to achieve a full utilization of it in the short run, thus lowering technical efficiency.

Finally, looking at the Schumpeter Mark II constant dummy, this indicates that efficiency change has been significantly more rapid for firms in the Schumpeter Mark I than in the Schumpeter Mark II. This provides further support for the third hypothesis put forward in section 3 (see hypothesis 3b).

< Table 5 here >

6. Conclusions

The paper has analysed the dynamics of productivity of Norwegian firms in the period 1998-2004, and it has investigated the relationships between TFP growth and technological regimes. The empirical analysis has proceeded in two steps. First, we have employed data envelopment analysis in order to decompose the growth of TFP into two distinct components, technical progress and efficiency change. Then, we have explored the determinants of these two components by estimating a model that links technological regime-related factors and a set of other firm-specific characteristics to the productivity performance of Norwegian enterprises.

Our main results can be summarized as follows. First, the productivity decomposition exercise indicates that in the period 1998-2004 TFP growth has mostly been obtained through technical progress, whereas technical efficiency has on average decreased.

The technological regime type of model that we have put forward to investigate the determinants of these two distinct components appears to perform reasonably well in the econometric estimations, and provides basic support for the first of our theoretical hypotheses (see section 3, hypothesis 1).

Specifically, both components of productivity growth are significantly related to the level of technological opportunities (as measured by the acquisition of external knowledge), other sources of opportunities within the same firm, the ability of the enterprise to increase market shares and entering new markets, as well as a set of other firm-specific characteristics such as size, export orientation and the average length of the product cycle.

Secondly, the econometric results also indicate that some of the explanatory variables in the model have different effects on the two distinct components of productivity growth. This provides support for the second hypothesis put forward by our theoretical framework (see section 3, hypothesis 2).

In particular, internal R&D efforts and the cumulativeness of R&D activities are important factors for the dynamics of technical progress but not for efficiency change. Among the external sources of opportunity, competitors on the same market are important for technical progress, whereas interacting with the consultants seems to constitute a more relevant factor to achieve efficiency improvements. Increases in the productive capacity of the firm are, quite obviously, positively related to technical progress but negatively linked to the efficiency component. Last, the level of TFP shows a strong negative (positive) relationship with technical progress (efficiency change), thus possibly suggesting a possible trade-off in the short-run between the efforts devoted to the introduction of new technologies and the achievement of high efficiency in the utilization of existing techniques.

Thirdly, the empirical results also provide support for the idea that the relationships between technological regimes, technical progress and efficiency changes work differently in different Schumpeterian patterns of innovation (see section 3, hypothesis 3). In the piecewise linear regression version of our econometric model, many of the explanatory variables turn out to have different estimated coefficients in the Schumpeter Mark I and in the Schumpeter Mark II regimes. This is particularly the case in the technical progress equation, where several regressors significantly differ among the regimes (e.g. cumulativeness, group structure, length of the product life, market location, lack of technological information as a main hampering factor).

These results also indicate that the technical progress component of TFP growth has proved to be significantly more dynamic for firms in the Schumpeter Mark II regime (hypothesis 3a), whereas the efficiency change component has been higher for enterprises in the Schumpeter Mark I type of markets (hypothesis 3b).

Our interpretation of this result is that the mechanism of productivity growth differs in the two Schumpeterian regimes. While Schumpeter Mark II markets are characterized by an oligopolistic structure where large incumbent innovators continuously and cumulatively push the technological frontier further (technical progress), firms in Schumpeter Mark I industries must pay close attention to make an efficient use of already available techniques (efficiency change), which is a crucial requirement to survive in competitive and turbulent markets.

Appendix: Empirical model and econometric issues

In order to analyse the relationship between TFP growth and innovation, we follow a *two-step empirical strategy*. The first step estimates TFP growth and decomposes it into two components: technical progress and efficiency change (see section 4). The second step uses these two components as dependent variables, and relates them to a set of innovation variables by means of a Heckman selection econometric model (see section 5).

A1. Step 1: the DEA empirical model

Data envelopment analysis (DEA) is a nonparametric method to estimate the production frontier and efficiency levels of a number of observed units (Farrell, 1957). In our paper (see section 4), we estimate the production frontier and efficiency of *n* firms belonging to each sector *j* for each period *t*.

In each industry, the production process may be described as follows. The *n* enterprises produce the output Y_i^t (where $Y_i^t \geq 0$) by using *m* inputs X_i^t (in our empirical exercise *m* equals 2, capital and labour). The *production set* Ω^t is defined as the set of physically attainable combinations $(X^t;Y^t)$, i.e. such that X^t can produce Y^t. For each firm *i*, the *Farrell output measure of efficiency* $E^t(X_i^t;Y_i^t)$ indicates the distance between the enterprise and the production frontier in its industry. If $E^t(X_i^t;Y_i^t) = 1$ the firm is output-efficient (i.e. it is a best-practice unit), otherwise it lies below the production frontier.

Given this efficiency measure, the *Malmquist productivity index* for firm *i* (Färe et al., 1994; Färe and Grosskopf, 1996) can be defined as:

$$M_i^t = [E^t(X_i^{t+1};Y_i^{t+1}) \,/\, E^t(X_i^t;Y_i^t)] \qquad (1)$$

where the numerator measures the efficiency change that the firm would need in order to achieve the combination $(X_i^{t+1};Y_i^{t+1})$ in the next period ($t+1$) given the technology available in the current period (t). Given M_i^t and M_i^{t+1}, the *Malmquist productivity change index* measures the growth of TFP between period t and $t+1$:

$$\Delta M_i(t;\, t+1) = \{[E^t(X_i^{t+1};Y_i^{t+1}) \,/\, E^t(X_i^t;Y_i^t)] \bullet [E^{t+1}(X_i^{t+1};Y_i^{t+1}) \,/\, E^{t+1}(X_i^t;Y_i^t)]\}^{½} \qquad (2)$$

This growth index can be decomposed into two parts:

$$EC_i(t;\, t+1) = [E^{t+1}(X_i^{t+1};Y_i^{t+1}) \,/\, E^t(X_i^t;Y_i^t)] \qquad (3)$$

$$TP_i(t;\, t+1) = \{[E^t(X_i^{t+1};Y_i^{t+1}) \,/\, E^{t+1}(X_i^{t+1};Y_i^{t+1})] \bullet [E^t(X_i^t;Y_i^t) \,/\, E^{t+1}(X_i^t;Y_i^t)]\}^{½} \qquad (4)$$

The first component measures the change of efficiency of firm i whereas the second is the technical progress component. These two components represent the dependent variables of our empirical study. However, since the production set Ω^t is unknown, we need an estimation of it before being able to calculate the efficiency measures and productivity components that have been defined here.

Simar and Wilson (2000) point out three general assumptions that are sufficient to specify a data generating process (DGP) for estimating the production set Ω^t: (1) free disposability and convexity of the production set; (2) i.i.d. sampling: the n observations are generated by i.i.d. random variables with a given probability density function $f(X^t;Y^t)$; (3) $E^t(X_i^t;Y_i^t)$ is differentiable in both inputs and output for all observations. In short, given these assumptions, the DGP is defined as: $P = P\ (\Omega^t; f(X^t;Y^t))$.

The DEA estimator of the production frontier, Ω^t_{DEA}, is obtained as the solution of the following linear programming problem:

$$\Omega^t_{\mathrm{DEA}} = \{ (X^t;Y^t) \mid \begin{cases} y \leq \sum (\eta_i \bullet Y_i) \\ x \geq \sum (\eta_i \bullet X_i) \\ \sum \eta_i = 1 \\ \eta_i \geq 0;\ i = 1, \ldots, n \ \} \end{cases} \tag{5}$$

Plugging Ω^t_{DEA} into $E^t(X_i^t;Y_i^t)$, we obtain $E^t_{\mathrm{DEA}}(X_i^t;Y_i^t)$, i.e. the DEA estimator of efficiency for a given firm *i* in period *t*. By using these estimated efficiency levels, we can then obtain estimates of the two productivity growth components defined above, efficiency change and technical progress: $EC_{iDEA}\,(t;\, t+1)$ and $TP_{iDEA}\,(t;\, t+1)$.

A2. Econometric issues and possible limitations of the DEA approach

Issue I: Sensitivity of efficiency estimates to the sampling variation of the frontier

Simar and Wilson (1998; 2000) point out that the DEA estimates of efficiency levels may be sensitive to the sampling variation of the production frontier. They therefore propose a bootstrap procedure that can be used for the inference process in relation to DEA estimates.

The general idea of this bootstrap procedure is to simulate the DGP and apply the DEA estimator to each simulated sample. The obtained estimates will tend to reproduce the sampling distribution of the DEA estimator, and can therefore be used to construct confidence intervals for $E^t_{\mathrm{DEA}}(X_i^t;Y_i^t)$. The procedure consists of three steps: (1) generate K samples S_k^* (k = 1, …, K); (2) for each k, calculate the pseudo estimates $\Omega_{k\,\mathrm{DEA}}^{t\;*}$ and $E_{k\,\mathrm{DEA}}^{t\;*}(X_i^t;Y_i^t)$; (3) use the empirical distribution of $E_{k\,\mathrm{DEA}}^{t\;*}(X_i^t;Y_i^t)$, for k = 1, …, K, for constructing confidence intervals for $E_{\mathrm{DEA}}^t(X_i^t;Y_i^t)$. Notice, however, that this bootstrap procedure is effective if we make use of a good estimator of the data generating process $P = P\,(\Omega^t;\, f(X^t;Y^t))$, which will not necessarily be the case in many empirical exercises.

An important econometric result is provided by Banker (1993), who demonstrates that, under rather general conditions, the DEA estimator is consistent. In short, the intuition of Banker's result can be summarized as follows. For each observation i, the estimated efficiency level is determined independently on the efficiency levels estimated for all other units. Hence, if the DEA is represented as a MLE model, the likelihood function is maximized in correspondence to the DEA estimator. In other words, the DEA estimator provides a MLE of the frontier and it is therefore a consistent estimator (for details and a proof of this result see Banker, 1993). For the specific exercise carried out in this paper, this result is important: since we are using a large and representative sample of Norwegian firms in each sector, the consistency property of the DEA estimator suggests that we can rely on the validity of our efficiency estimates.

Issue II: Super-efficient outliers

Cazals et al. (2002) and Simar (2003) observe that DEA estimates could be very sensitive to the presence of super-efficient outliers (i.e. observations that lie substantially above the other production units). It is therefore important to check for the presence of outliers and make sure that the DEA estimates are carried out without them. In our paper, we have taken care of this issue by carrying out a careful visual inspection of outliers. Specifically, after obtaining a first set of DEA efficiency estimates for each industry, we have identified the units whose single-input productivities (i.e. the productivity with respect to either capital or labour) lie substantially above those for the other firms. We have then singled out and deleted these outliers and repeated the DEA estimations without them.

Simar (2003) has recently proposed an alternative outliers detection procedure based on the concept of *order-m frontier of Ω*. Cazals et al. (2002) define the order-m frontier of Ω, Ω_m, as the expected value of the maximum of m random variables generated by the DGP P. m is a trimming parameter, i.e. a fixed integer ($1 \leq m \leq n$) such that, as the parameter increases, Ω_m tends to the true frontier Ω. If some observed point remains above Ω_m even when m increases, then this observation is a possible outlier and needs to be inspected more carefully.

Simar's method of outliers detection consists of the following steps: (1) for each observation, compute the *leave-one-out* efficiency score of the order-m frontier (i.e. the efficiency score obtained by deleting that specific observation); (2) repeat step 1 for several increasing values of m, and report all results (for each observation and different values of m) in a table; (3) focus on those observations for which the values of the order-m efficiency scores are substantially smaller than 1; (4) delete these super-efficient outliers and repeat the DEA estimations without these observations.

A3. Step 2: the Heckman selection model

The second step of our empirical analysis (see section 5) uses the two productivity growth components estimated through DEA as dependent variables, and relates them to a set of innovation variables by means of a Heckman selection econometric model. The Heckman estimation method corrects for the possible presence of selection-bias that is caused by the exclusion of non-innovative firms from the sample. It is a two-stage procedure: the first stage estimates a selection equation, which investigates the factors explaining the probability that a firm is an innovator, whereas the second stage studies the links between innovation and productivity growth. The selection equation (stage 1) is given by:

$$I_i^* = W_i \bullet \lambda + \zeta_i \qquad (6)$$

where I_i^* is an innovation (latent) variable and W_i is a set of regressors determining whether a firm innovates. Based on this, we then construct an innovator dummy variable I_i that is defined as follows: if $I_i^* > 0 \Rightarrow I_i = 1$; otherwise $I_i = 0$.

In the second stage of the Heckman procedure, the two productivity equations refer to the technical progress (TP_i) and efficiency change (EC_i) components respectively:

$$TP_i = Z_i \bullet \alpha + \varphi_i \qquad (7)$$

$$EC_i = Z_i \bullet \beta + \omega_i \qquad (8)$$

These two productivity components are regressed on the set of explanatory variables Z_i by using OLS, and are defined only for those observations for which $I_i = 1$. Among the other regressors, these equations also include the inverse Mills ratio calculated from the 1st stage of the Heckman procedure that corrects for the sample selection bias.

Issue III: Bias and consistency of the two-step procedure

The two-step empirical strategy followed in this paper (DEA in the first and OLS in the second step) is well rooted in the productivity literature. However, Simar and Wilson (2007) have recently pointed out a possible econometric problem with this strategy. The DEA estimates of efficiency may be serially correlated, because all $E^t_{DEA}(X_i^t;Y_i^t)$, and hence all the error terms in the second step of the procedure, depend on all other observations $(X_l^t;Y_l^t)$ (for all $l \neq i$). The second step of the procedure may therefore be biased. Simar and Wilson (2007) propose to correct for this by including a bootstrap-based estimate of the bias in the second step of the analysis.

A different approach to this issue is provided by Banker and Natarajan (2008). The main idea of this recent work is to present DEA as a stochastic (rather than deterministic) framework, and show that the two-step procedure (DEA followed by OLS) is a valid (consistent) approach to estimate the effects of the contextual variables Z on firms' productivity. Banker and Natarajan (2008) assume that the *n* observations are generated from the real production function τ plus an error term:

$$Y_i^t = \tau\,(X_i^t) \bullet \varepsilon_i^t \tag{9}$$

The error term is specified as a random variable composed of three parts:

$$\varepsilon_i^t = v_i^t - u_i^t - \sum \delta_s \bullet Z_{is}^t \tag{10}$$

The first part is a two-sided random noise with a finite upper bound; the second is the technical efficiency term (that has a one-sided distribution); and the third represents the set of *s* contextual variables Z. Banker and Natarajan (2008) show that, under very general conditions, the OLS in the second step is a consistent estimator of the impact of the contextual variables Z on productivity. This result is important for our paper. In fact, similarly to what pointed out above, our empirical exercise makes use of a large and representative sample of firms in each sector, so that the consistency of the two-step procedure suggests the validity of our efficiency estimates.

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References

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P. (2005): 'Competition and innovation: an inverted U relationship', *Quarterly Journal of Economics*, 120 (2), 701-728.

Banker, R. (1993): 'Maximum likelihood, consistency and data envelopment analysis: a statistical foundation", *Management Science*, 39 (10), 1265-1273.

Banker, R. and Natarajan, R. (2008): 'Evaluating contextual variables affecting productivity using data envelopment analysis', *Operations Research*, 56 (1), 48-58.

Bartelsman, E. J. and Doms, M. (2000): 'Understanding productivity: lessons from longitudinal microdata', *Journal of Economic Literature*, 38 (3), 569-594.

Breschi, S., Malerba, F., Orsenigo, L. (2000): 'Technological regimes and Schumpeterian patterns of innovation', *Economic Journal*, 110, 388-410.

Cainelli, G., Evangelista, R. and Savona, M. (2006): 'Innovation and economic performance in services: a firm-level analysis', *Cambridge Journal of Economics*, 30, 435-458.

Castellacci, F. (2007): 'Technological regimes and sectoral differences in productivity growth', *Industrial and Corporate Change*, 16 (6), 1105-1145.

Castellacci, F. (2008a): 'Innovation and the competitiveness of industries: comparing the mainstream and the evolutionary approaches', *Technological Forecasting and Social Change*, 75, 984-1006.

Castellacci, F. (2008b): 'Technological paradigms, regimes and trajectories: manufacturing and service industries in a new taxonomy of sectoral patterns of innovation", *Research Policy*, 37, 978-994.

Castellacci, F., Clausen, T., Nås, S.O. and Verspagen, B. (2009): 'Historical fingertips? A taxonomy of innovation in Norway', in Fagerberg, J., Mowery, D. and Verspagen, B. (Eds.), *Innovation, Path-dependency and Policy: the Norwegian Case*, Oxford University Press.

Cazals, C., Florens, J. and Simar, L. (2002): ‘Nonparametric frontier estimation: a robust approach’, *Journal of Econometrics*, 106, 1-25.

Caves, R. (1998): ‘Industrial organization and new findings on the turnover and mobility of firms’, *Journal of Economic Literature*, XXXVI, 1947-1982.

Cefis, E. and L. Orsenigo (2001), ‘The persistence of innovative activities: a cross-countries and cross-sectors comparative analysis’, *Research Policy*, 30, 1139-1158.

Cohen, W. M. and R. Levin (1989), ‘Empirical studies of innovation and market structure’, in R. Schmalensee and R.D. Willig (Eds.), *Handbook of Industrial Organization, Volume II*, North Holland.

Crepon, B., Duguet, E. and Mairesse, J. (1998): ‘Research, innovation and productivity: an econometric analysis at the firm level’, *Economics of Innovation and New Technology*, 7 (2), 115-158.

Crespi, G., Criscuolo, C. Haskel, J. and Slaughter, M. (2007): ‘Productivity Growth, Knowledge Flows and Spillovers’ *CEP Discussion Papers* 785, Centre for Economic Performance, LSE.

Dosi, G. (1988), ‘Sources, procedures, and microeconomic effects of innovation’, *Journal of Economic Literature*, XXVI, 1120-1171.

Dosi, G., Marengo, L. and Pasquali, C. (2006): ‘How much should society fuel the greed of innovators? On the relations between appropriability, opportunities and rates of innovation’, *Research Policy*, 35 (8), 1110-1121.

Duguet, E. (2006): ‘Innovation height, spillovers and TFP growth at the firm level: Evidence from French manufacturing”, *Economics of Innovation and New Technology*, 15 (4&5), 415-442.

Färe, R. and Grosskopf, M. N. (1996): *Intertemporal Production Frontiers: With Dynamics DEA*, Kluwer Academic, Boston.

Färe, R., Grosskopf, M. N., Norris, M. and Zhang, Z. (1994): ‘Productivity growth, technical progress, and efficiency changes in industrialized countries’, *American Economic Review*, 84 (1), 66-83.

Farrell, M. J. (1957): ‘The measurement of productive efficiency’, *Journal of the Royal Statistical Society*, 120 (3), 253-281.

Foster, L., Haltiwanger, J. and C. J. Krizan (1998), ‘Aggregate productivity growth: lessons from microeconomic evidence’, *NBER Working Paper*, No. 6803.

Griffith, R., Huergo, H., Mairesse, J. and Peters, B. (2006): ‘Innovation and Productivity Across Four European Countries’, *Oxford Review of Economic Policy*, 22(4), 483-498.

Griliches, Z. (1979): ‘Issues in assessing the contribution of research and development to productivity growth’, *The Bell Journal of Economics*, 10, 92-116.

Hall, B. and Mairesse, J. (2006): ‘Empirical studies of innovation in the knowledge-driven economy’, *Economics of Innovation and New Technology*, 15, (4&5), 289-299.

Heshmati, A. (2003): ‘Productivity growth, efficiency and outsourcing in manufacturing and service industries’, *Journal of Economic Surveys*, 17 (1), 79-112.

Janz, N., Lööf, H. and Peters, B. (2003): ‘Firm Level Innovation and Productivity: Is there a Common Story Across Countries?’ *ZEW Discussion Papers* 03-26.

Laursen, K. and V. Meliciani (2002), ‘The relative importance of international *vis-à-vis* national technological spillovers for market share dynamics’, *Industrial and Corporate Change*, 11, 875-894.

Lee, K. and C. Lim (2001), ‘Technological regimes, catching-up and leapfrogging: findings from the Korean industries’, *Research Policy*, 30, 459-483.

Los, B. and B. Verspagen (2004), ‘Technology spillovers and their impact on productivity’, in H. Hanusch and A. Pyka (eds.), *Elgar Companion to Neo-Schumpeterian Economics*, Edward Elgar: Cheltenham, UK.

Lotti, F. (2007): ‘Firm Dynamics in Manufacturing and Services: a Broken Mirror?’, *Industrial and Corporate Change*, 16, 347-369.

Lööf, H., Heshmati, A., Asplund, R. and Nås, S. O. (2001): ‘Innovation and Performance in Manufacturing Industries: A Comparison of the Nordic Countries’, *Working Paper Series in Economics and Finance* 0457, Stockholm School of Economics.

Lööf, H. and Heshmati, A. (2006): ‘On the relationship between innovation and performance: A sensitivity analysis’, *Economics of Innovation and New Technology*, 15 (4&5), 317-344.

Malerba, F. (2002): ‘Sectoral systems of innovation and production’, *Research Policy*, 31 (2), 247-264.

Malerba, F. and F. Montobbio (2003): ‘Exploring factors affecting international technological specialization: the role of knowledge flows and the structure of innovative activity’, *Journal of Evolutionary Economics*, 13, 411-434.

Malerba, F., Orsenigo, L. (1995): ‘Schumpeterian patterns of innovation’, *Cambridge Journal of Economics*, 19, 47-65.

Malerba, F., Orsenigo, L. (1996): ‘Schumpeterian patterns of innovation are technology-specific’, *Research Policy*, 25, 451-478.

Marsili, O., Verspagen, B. (2002): ‘Technology and the dynamics of industrial structure: an empirical mapping of Dutch manufacturing’, *Industrial and Corporate Change*, 11 (4), 791-815.

Nelson, R.R. and S.G. Winter (1982): *An Evolutionary Theory of Economic Change*, The Belknap Press of Harvard University Press, Cambridge, USA.

Nishimizu, M. and Page, J.M. (1982): ‘Total factor productivity growth, technical progress and technical efficiency change: dimensions of productivity change in Yugoslavia, 1965-78’, *Economic Journal*, 92, 920-936.

Parelman, S. (1995): ‘R&D, technological progress and efficiency change in industrial activities’, *Review of Income and Wealth*, 41 (3), 349-366.

Parisi, M. L., Schiantarelli, F. and Sembenelli, A. (2006): ‘Productivity, innovation and R&D: Micro evidence for Italy’, *European Economic Review*, 50 (8), 2037-2061.

Park, K. and Lee, K. (2006): ‘Linking the technological regime to the technological catch-up: analysing Korea and Taiwan using US patent data’, *Industrial and Corporate Change*, 15 (4), 715-753.

Reichstein, T. and Salter, A. (2006): ‘Investigating the sources of process innovation among UK manufacturing firms’, *Industrial and Corporate Change*, 15 (4), 653-682.

Santarelli, E. and Vivarelli, M. (2007), ‘Entrepreneurship and the process of firms’ entry, survival and growth’, *Industrial and Corporate Change*, 16, 455-488.

Schumpeter, J. (1934), *The Theory of Economic Development*, Harvard University Press, Cambridge, USA.

Schumpeter, J. (1943), *Capitalism, Socialism and Democracy*, Harper, New York.

Simar, L. (2003): ‘Detecting outliers in frontier models: a simple approach’, *Journal of Productivity Analysis*, 20, 391-424.

Simar, L. and Wilson, P. (1998): ‘Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models’, *Management Science*, 44 (1), 49-61.

Simar, L. and Wilson, P. (2000): ‘Statistical inference in nonparametric frontier models: the state of the art’, *Journal of Productivity Analysis*, 13, 49-78.

Simar, L. and Wilson, P. (2007): ‘Estimation and inference in two-stage, semi-parametric models of production processes’, *Journal of Econometrics*, 136, 31-64.

Srholec, M. and Verspagen, B. (2008): ‘The voyage of the beagle in innovation systems land. Explorations on sectors, innovation, heterogeneity and selection’, UNU-MERIT Working Paper No. 8/2008.

Van Dijk, M. (2000): ‘Technological Regimes and Industrial Dynamics: the Evidence from Dutch Manufacturing’, *Industrial and Corporate Change*, 9 (2), 173-194.

Van Leuwen, G. and L. Klomp (2006): ‘On the contribution of innovation to multi-factor productivity growth’, *Economics of Innovation and New Technology*, 15 (4&5), 367-390.

Von Tunzelmann, N. and V. Acha (2005), ‘Innovation in “low-tech” industries’, in J. Fagerberg, D. C. Mowery and R. R. Nelson (eds.), *The Oxford Handbook of Innovation*, Oxford University Press: Oxford.

Von Tunzelmann, N., Malerba, F., Nightingale, P. and Metcalfe, S. (2007): ‘Technological paradigms: past, present and future’, *Industrial and Corporate Change*, 17 (3), 467-484.

Wieser, R. (2005): ‘Research and development productivity and spillovers: empirical evidence at the firm level’, *Journal of Economic Surveys*, 19 (4), 587-621.

Winter, S. G. (1984), ‘Schumpeterian Competition in Alternative Technological Regimes’, *Journal of Economic Behavior and Organization*, 5, 137-158.

Winter, S. (2006): ‘Toward a neo-Schumpeterian theory of the firm’, *Industrial and Corporate Change*, 15 (1), 125-141.

Zheng, J., Liu, X. and Bigsten, A. (1998): ‘Ownership Structure and Determinants of Technical Efficiency: An Application of Data Envelopment Analysis to Chinese Enterprises (1986-1990)’ *Journal of Comparative Economics*, 26 (3), 465-484.

Zheng, J., Liu, X. and Bigsten, A. (2003): ‘Efficiency, technical progress, and best practice in Chinese state enterprises (1980–1994)’, *Journal of Comparative Economics*, 31 (1), 134-152.

Table 1: Decomposition of total factor productivity growth of Norwegian enterprises, average by 2-digit industries and for each period

Industries	1998-2001			2002-2004		
	Malmquist TFP Index	**Efficiency change**	**Technical progress**	**Malmquist TFP Index**	**Efficiency change**	**Technical progress**
Mining and quarrying	1.0402	0.9706	1.0850	1.1209	1.0528	1.0756
Food and beverages	1.0808	0.9861	1.1197	1.4167	1.1677	1.2137
Textiles	1.0544	1.0108	1.0542	1.0829	0.9056	1.3152
Wearing	1.0451	0.9272	1.1464	1.0102	0.9506	1.0740
Leather and footwear	1.1029	0.9694	1.1551	1.2436	1.1141	1.1031
Wood and related	1.0502	0.9488	1.2139	1.1179	0.9119	1.3130
Pulp and paper	1.0648	0.8965	1.2589	1.0269	0.9312	1.1006
Printing and publishing	1.0388	0.9477	1.2569	1.0998	0.9886	1.1272
Other non-metallic mineral products	1.0694	0.9323	1.1825	1.0416	0.8077	1.3836
Basic metals	1.0965	1.0111	1.1027	1.0290	0.7896	1.4136
Fabricated metal products	1.0360	0.9407	1.1288	1.1427	0.9094	1.3796
Machinery and equipment	1.0625	0.9190	1.2129	1.0726	0.8521	1.3848
Electrical	1.0765	0.9700	1.1158	1.1552	1.0266	1.4619
Radio and television	1.0797	0.8319	1.5832	1.0345	0.9677	1.1141
Medical and optical	1.0703	0.9649	1.1574	1.0978	0.9429	1.2283
Motor vehicles	1.0743	1.0277	1.0536	1.1802	0.9352	1.2910
Other transport equipment	1.1147	1.0143	1.1069	1.0934	0.9452	1.2264
Furniture	1.0377	0.8612	1.2980	1.0824	0.8285	1.4526
Recycling	1.1025	0.8621	1.3769	1.2474	0.8674	1.5475
Construction	1.0406	0.9429	1.1224	1.0531	0.9702	1.0942
Wholesale trade	1.1174	0.9713	1.1535	1.0927	1.0189	1.0934
Retail trade	1.0286	0.9256	1.1195	1.0875	0.8904	1.2316
Land transport	1.0088	0.9314	1.0897	1.0699	0.9873	1.0900
Sea transport	0.9232	0.6663	1.4390	1.0260	0.7836	1.3699
Air transport	1.2222	1.1336	1.0928	0.9239	0.8793	1.0641
Other transport services	0.9628	0.8697	1.1208	1.1218	0.9369	1.2132
Telecommunication	0.8953	0.6626	1.3590	1.3818	1.0378	2.0334
Real estate activities	0.9997	0.8775	1.1792	1.0123	0.9534	1.0630
Renting of machinery and equipment	0.9955	0.9209	1.0978	0.9550	0.7816	1.2706
Computing and software	1.0333	0.7846	1.3729	1.0410	0.7824	1.4509
Research and development	0.9686	0.9302	1.0439	1.0011	0.8580	1.2188
Other business services	1.0614	0.9762	1.1021	1.0364	0.9568	1.1001
Average	*1.0436*	*0.9242*	*1.1772*	*1.1016*	*0.9319*	*1.2632*

Table 2: Descriptive statistics: Characteristics of innovative and non-innovative samples, 1998-2000 (CIS3) and 2002-2004 (CIS4)

	1998-2000 (CIS3)					**2002-2004 (CIS4)**				
	Innovative sample (N=417)		**Non-innovative sample (N=596)**		**Mann-Whitney U test [a]**	**Innovative sample (N=754)**		**Non-innovative sample (N=899)**		**Mann-Whitney U test [a]**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**z**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**z**
TFP level	0.53	0.28	0.48	0.25	-2.51**	0.38	0.22	0.38	0.22	-0.09
Employment	223	413	116	243	-7.62***	153	345	92	206	-7.48***
Group	0.77	0.42	0.66	0.47	-3.97***	0.62	0.49	0.55	0.50	-2.59***
Product life	4.76	1.25	5.24	1.20	+7.55***	4.59	1.34	5.06	1.41	+10.1***
Market location	2.96	1.03	2.35	1.14	-8.55***	2.09	0.91	1.63	0.77	-10.6***
Export intensity	0.35	0.51	0.16	0.32	-9.29***	0.24	0.35	0.11	0.35	-11.8***

[a] Mann-Whitney U test for the difference between the two samples. The values reported in the column are the z scores from the test. Positive (negative) z scores indicate that the variable is smaller (greater) for innovators than for non-innovators. Significance levels: *** 1%; ** 5%; * 10%.

Table 3: A comparison of Schumpeter Mark I and Schumpeter Mark II sectors, 1998-2000 (CIS3) and 2002-2004 (CIS4)

	1998-2000 (CIS3)					**2002-2004 (CIS4)**				
	Schumpeter Mark II (N=276)		**Schumpeter Mark I (N=737)**		**Mann-Whitney U test [a]**	**Schumpeter Mark II (N=472)**		**Schumpeter Mark I (N=1181)**		**Mann-Whitney U test [a]**
	Mean	**CV**	**Mean**	**CV**	**U test [b]**	**Mean**	**CV**	**Mean**	**CV**	**U test [b]**
TFP growth	1.007	0.77	1.035	0.35	+2.51**	1.039	0.39	1.064	0.33	+3.63***
Efficiency change	0.924	0.84	0.962	0.36	+2.88***	0.721	0.44	0.858	0.37	+9.43***
Technical progress	1.124	0.20	1.095	0.17	-4.02***	1.553	0.34	1.339	0.38	-12.68***
TFP level	0.50	0.61	0.50	0.49	+1.26	0.35	0.66	0.40	0.55	+5.18***
Employment	228	1.98	134	1.96	-4.33***	170	2.01	100	2.48	-7.29***
Group	0.74	0.59	0.69	0.67	-1.58	0.64	0.75	0.56	0.88	-2.93***
Product life	5.06	0.24	5.02	0.25	-0.33	4.82	0.30	4.80	0.29	-0.96
Market location	2.76	0.43	2.55	0.44	-3.42***	2.07	0.45	1.74	0.47	-6.33***
Export intensity	0.35	1.57	0.20	1.78	-4.62***	0.22	1.73	0.15	2.32	-1.99**
Cumulativeness	0.55	1.39	0.43	1.64	-2.42**	0.61	1.23	0.55	1.41	-2.08**
R&D intensity	0.37	2.55	0.46	2.51	-1.76*	0.52	2.16	0.65	2.29	-1.70*

[a] Mann-Whitney U test for the difference between the two industry groups. The values reported in the column are the z scores from the test. Positive (negative) z scores indicate that the variable is smaller (greater) for Schumpeter Mark II than for Schumpeter Mark I sectors. Significance levels: *** 1%; ** 5%; * 10%.

Table 4: The determinants of technical progress[a] – Results of Heckman two-step estimations

		Selection equation	**Step 2 equation**		
	Dependent variable	Innovator dummy	Technical progress	Technical progress	Technical progress
	TFP level		-0.475	-0.552	-0.426
			(7.12)***	(6.78)***	(4.32)***
	Employment (log)	0.363	0.011	0.118	0.082
		(9.64)***	(0.49)	(6.38)***	(4.51)***
	Group	0.279	-0.036	0.040	-0.091
		(3.25)***	(0.80)	(0.69)	(1.46)
Firm-specific factors	Product life	-0.160	-0.020	0.016	-0.066
		(5.96)***	(1.38)	(0.92)	(3.38)***
	Export intensity	0.100	0.014	-0.050	-0.007
		(0.88)	(0.28)	(0.71)	(0.10)
	Market location	0.129	0.014	0.119	0.157
		(2.87)***	(0.65)	(4.49)***	(5.61)***
	H-Costs	0.198			
		(4.85)***			
	H-Personnel	0.109	-0.061	-0.068	-0.067
Hampering factors (H)		(1.82)*	(2.61)***	(2.26)**	(2.38)**
	H-TechInfo	0.121	0.045	0.104	0.122
		(1.67)*	(1.70)*	(3.16)***	(3.51)***
	H-OtherInfo	0.151			
		(2.24)**			
Cumulativeness	Continuous R&D		-0.010	0.066	0.107
			(0.48)	(2.38)**	(3.37)***
Technological opportunity levels	R&D intensity		0.007	0.023	0.017
			(0.76)	(1.89)*	(1.45)
	Other external knowledge		0.109	0.304	0.293
			(1.22)	(2.54)**	(2.55)**
	S-Internal		0.022	0.095	0.082
			(1.22)	(3.92)***	(3.55)***
	S-Group		0.006	-0.022	-0.014
			(0.40)	(1.08)	(0.71)
	S-Suppliers		0.000	0.017	0.009
			(0.02)	(0.78)	(0.44)
	S-Users		-0.022	0.022	0.007
External sources of opportunities (S)			(1.16)	(0.90)	(0.31)
	S-Competitors		0.032	0.039	0.029
			(1.74)*	(1.58)	(1.21)
	S-Consultants		-0.001	0.015	-0.007
			(0.07)	(0.57)	(0.24)
	S-Private R&D labs		-0.007	-0.020	-0.013
			(0.31)	(0.62)	(0.43)
	S-Universities		-0.021	-0.044	-0.048
			(0.81)	(1.27)	(1.46)
	S-Public research institutes		0.011	0.004	0.033
			(0.48)	(0.12)	(1.07)
	A-Trademark		0.053	0.071	0.070
			(1.49)	(1.45)	(1.52)
	A-Patent		-0.007	-0.035	-0.052
Appropriability (A)			(0.20)	(0.68)	(1.05)
	A-Secrecy		-0.024	-0.049	-0.045

			(0.73)	(1.06)	(1.02)
	A-Complex design		-0.032	-0.028	-0.033
			(0.84)	(0.55)	(0.67)
	E-Market orientation		0.020	0.049	0.036
			(1.20)	(2.13)**	(1.65)*
Effects of innovation (E)	E-Productive capacity		0.027	0.041	0.052
			(1.45)	(1.59)	(2.12)**
	E-Labour costs		-0.029	0.003	-0.015
			(1.52)	(0.10)	(0.58)
	SMII-Constant dummy			0.137	1.427
				(3.06)***	(6.86)***
	SD- TFP level				-0.225
					(1.51)
	SD-Group				0.295
					(2.78)***
	SD-Product life				-0.146
					(5.01)***
Schumpeter Mark II slope dummies (SD)	SD-Market location				-0.174
					(4.24)***
	SD-Cumulativeness				-0.200
					(3.51)***
	SD-S-Consultants				0.058
					(1.15)
	SD-H-TechInfo				-0.171
					(3.22)***
	Mills ratio		0.025	0.226	0.132
			(0.28)	(4.12)***	(2.41)**
	Rho		0.074	0.449	0.286
	Sigma		0.338	0.505	0.460
	Time dummy	-0.436	-0.291	-0.435	-0.398
		(5.14)***	(6.54)***	(8.29)***	(8.07)***
	Industry dummies	Yes	Yes	No	No
	Wald χ^2		4236.01***	1776.36***	2103.58***
	Number of observations	1840	1840	1840	1840
	Censored	1202	1202	1202	1202
	Uncensored	638	638	638	638

[a] T-statistics between brackets. Significance levels: *** 1%; ** 5%; * 10%.

Table 5: The determinants of efficiency change[a] – Results of Heckman two-step estimations

	Dependent variable	**Selection equation** Innovator dummy	**Step 2 equation** Efficiency change	Efficiency change	Efficiency change
Firm-specific factors	TFP level		0.574	0.542	0.448
			(11.4)***	(10.6)***	(6.96)***
	Employment (log)	0.363	-0.040	0.043	0.045
		(9.64)***	(2.20)**	(3.63)***	(3.76)***
	Group	0.279	0.017	0.094	0.100
		(3.25)***	(0.49)	(2.56)**	(2.72)***
	Product life	-0.160	0.000	-0.014	-0.017
		(5.96)***	(0.02)	(1.28)	(1.54)
	Export intensity	0.100	-0.088	-0.030	-0.033
		(0.88)	(2.16)**	(0.66)	(0.72)
	Market location	0.129	-0.022	0.024	0.029
		(2.87)***	(1.40)	(1.41)	(1.69)*
Hampering factors (H)	H-Costs	0.198			
		(4.85)***			
	H-Personnel	0.109	-0.008	0.044	0.043
		(1.82)*	(0.47)	(2.26)**	(2.20)**
	H-TechInfo	0.121	-0.025	0.039	0.042
		(1.67)*	(1.21)	(1.84)*	(1.98)**
	H-OtherInfo	0.151			
		(2.24)**			
Cumulativeness	Continuous R&D		-0.043	-0.016	-0.014
			(2.80)***	(0.99)	(0.87)
Technological opportunity levels	R&D intensity		-0.003	0.001	0.000
			(0.40)	(0.10)	(0.02)
	R&D purchase		0.102	0.114	0.120
			(1.74)*	(1.80)*	(1.91)*
External sources of opportunities (S)	S-Internal		0.018	0.027	0.028
			(1.35)	(1.84)*	(1.89)*
	S-Group		-0.008	-0.010	-0.011
			(0.75)	(0.83)	(0.93)
	S-Suppliers		0.001	0.000	0.018
			(0.05)	(0.02)	(1.16)
	S-Users		-0.015	0.004	-0.001
			(1.03)	(0.29)	(0.05)
	S-Competitors		-0.007	-0.009	-0.002
			(0.55)	(0.62)	(0.16)
	S-Consultants		0.040	0.026	0.026
			(2.77)***	(1.63)	(1.66)*
	S-Private R&D labs		0.001	-0.002	-0.002
			(0.09)	(0.11)	(0.09)
	S-Universities		-0.020	-0.014	-0.013
			(1.03)	(0.64)	(0.59)
	S-Public research institutes		0.000	-0.001	-0.001
			(0.03)	(0.07)	(0.07)
Appropriability (A)	A-Trademark		0.018	-0.003	-0.005
			(0.68)	(0.11)	(0.18)
	A-Patent		-0.003	-0.016	-0.158
			(0.11)	(0.51)	(0.49)
	A-Secrecy		0.025	0.035	0.033

			(1.00)	(1.24)	(1.15)
	A-Complex design		-0.016	-0.038	-0.039
			(0.58)	(1.19)	(1.22)
	E-Market orientation		0.008	0.028	0.020
			(0.61)	(1.99)**	(1.23)
Effects of innovation (E)	E-Productive capacity		-0.025	-0.030	-0.032
			(1.74)*	(1.88)*	(2.02)**
	E-Labour costs		0.018	0.032	0.033
			(1.25)	(1.98)**	(2.07)**
	SMII-Constant dummy			-0.074	-0.128
				(2.57)***	(1.63)
	SD- TFP level				0.221
					(2.33)**
Schumpeter Mark II slope dummies (SD)	SD-S-Suppliers				-0.056
					(2.10)**
	SD-E-Market orientation				0.035
					(1.29)
	Mills ratio		-0.099	0.237	0.251
			(1.47)	(6.89)***	(7.09)***
	Rho		-0.374	0.691	0.725
	Sigma		0.266	0.342	0.346
	Time dummy	-0.436	0.094	0.000	-0.003
		(5.14)***	(2.78)***	(0.01)	(0.10)
	Industry dummies	Yes	Yes	No	No
	Wald χ^2		2379.55***	1465.17***	1465.48***
	Number of observations	1840	1840	1840	1840
	Censored	1202	1202	1202	1202
	Uncensored	638	638	638	638

[a] T-statistics between brackets. Significance levels: *** 1%; ** 5%; * 10%.