A Generalized Knowledge Production Function

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ABSTRACT

This paper presents a generalized production model based on the knowledge production function. The model allows the relationships between corporate competitiveness strategy, innovation, efficiency, productivity growth and outsourcing to be investigated at the firm level in a number of steps. First, in reviewing recent developments of researches on the above relationships, provide discussion on data and the methods of measuring these variables. Second, depending on availability of information, different measures are transferred into single multidimensional index of corporate strategy using principal component analysis. Third, stochastic frontier production function and factor productivity analysis are used to estimate the efficiency and factor productivity growth at the firm level. Fourth, the causal relationships between the five variables of interest are established and modelled. Finally, given the direction of causality, the implications of the findings for estimation of the relationship are discussed. For the empirical analysis we use Swedish firm-level innovation survey data covering both manufacturing and service sectors.

Keywords: Competition, innovation, outsourcing, productivity, efficiency, causality, firm

JEL Classification Numbers: C31, C52, D24, L10, L60, L80, O31

1. INTRODUCTION

The theoretical and empirical literatures on growth, productivity, efficiency and competition in industrial production at different level of aggregation are voluminous. In recent years, production, research as well as technology outsourcing has expanded much. The empirical evidence on technology outsourcing is oftenly based on aggregate country- or industry level-data and originate from industrial countries. While growth and competitiveness issues have mainly been applicable to country studies (Barro and Sala-i-Martin, 1995), the productivity and efficiency studies have been mainly micro oriented (Hulten 2000; Bartelsman and Doms, 2000; Coelli et al., 1998; Kumbhakar and Lovell, 2000; Heshmati 2003). The efficiency and productivity issues are frequently used in performance studies heavily concentrated on agriculture and manufacturing sectors and services. In recent years the methods have intensively been used in the evaluation performance in provision of private and public services foremost in provision of health care, banking and education. For examples of such studies see e.g. Griliches (1992), Solow (1992), Berger and Humphrey (1997), and Balk (1998), special issues of journals edited by Griliches and Mairesse (1993) and Berndt et al. (1992), and for a recent survey on the issue see Heshmati (2003).

The growing importance of the service sector in recent decades as a result of increased outsourcing activities and subsequent transfer of employment opportunities from manufacturing to the service sector has induced increasing concern about its performance. In general manufacturing is seen as the progressive and technologically advanced sector, while the labour intensive service sector is seen as stagnant. The service sector has grown much faster than the goods sector with expected negative impacts on the economic growth (Baumol 1967; Baumol et al., 1985). The negative effect is due to differences in labour intensity between the two sectors, but the gap is reducing as a result of advanced technology targeting production of services.

Although there exists a comprehensive literature on the issues of growth, productivity, efficiency, competition and innovation on each subject separately, very little can be found on their linkages and causal relationships. This paper contributes to the literature by empirically investigating such multi-dimensional causal relationships among the above variables. Thus, this paper is an attempt to fill the gap in the literature by investigating the relationship between corporate competitiveness strategy, efficiency, productivity growth, innovation and outsourcing. Performance is measured in several ways at the firm level. First, it is based on technical efficiency, defined as capacity to produce maximum possible output from a given set of inputs and available technology (Aigner et al. 1997; and Battese and Coelli 1995). Second, it is based on growth defined as factor productivity changes in output over time (Good et al. 1997; Kumbhakar et al. 1999). Third, innovation activities are measured based on innovation inputs and innovation outputs (Crépon et al. 1998; and Lööf and Heshmati 2006). Finally, measure of competitiveness is obtained from a set of factors important to the firms' competitive strategy (Nayyar 1993). Outsourcing is used to describe all the subcontracting relationships between firms and external suppliers. Thus as a starting point we follow the substitution- and abstention-based definitions of outsourcing (see e.g. Gilley and Rasheed 2000; Eggert and Falkingner 2003; Fixler and Siegel 1999).

The objective is not to provide a comprehensive review of the voluminous literature on each subject, rather seek instead to briefly overview recent contributions to literature and its developments with regards to the causal relationship between these performance indicators and strategy and outsourcing. The main focus is on the empirical analysis of the above relationship at the micro level based on unique innovation survey data.

In doing so, this paper presents a generalized production model based on the knowledge production function (Pakes and Griliches 1984; Griliches 1990). The model allows the relationships between corporate competitiveness strategy, innovation, efficiency, productivity growth and outsourcing to be investigated at the firm level. The overall procedure involves a number of steps. First, in addition to the reviewing of recent developments of researches on the above relationships, this paper provides a discussion on data and the methods of measuring the above variables. Second, depending on availability of information, different measures are transferred into single multidimensional index of corporate strategy using principal component analysis. Third, stochastic frontier production function and factor productivity analysis are used to estimate the efficiency and single and total factor productivity growth at the firm level. Fourth, the causal relationships between the five variables of interest are established and modelled. In the final step, given the direction of causality, the implications of the findings for estimation of the relationship are discussed in details. For the empirical analysis we use Swedish firm-level innovation survey data covering both manufacturing and service sectors from the period1996-1998.

The remainder of the paper is organised as follows. Section 2 introduces the methodologies used. The focus is in particular on the concepts of competitiveness, various performance measures, innovation and outsourcing and discusses their theoretical linkages. In Section 3, we describe the innovation survey data used in the empirical analysis. Section 5 outlines the empirical relationship between the above indicators and detailed specification of the model is discussed in Section 5. The empirical results concerning the relationship between the indicators are discussed in Section 6. We present possible extension of the current approach to improve consistency and usefulness of the techniques used to study causal relationships between our indicators. Section 7 summarises the main findings and draws conclusions.

2. METHODOLOGIES

Several methodologies are used to complete this study. These include: measurement and analysis of outsourcing activities, production efficiency, factor productivity growth, competitive strategy and innovativeness. A brief review of the development of the literatures is given below.

2.1 Productive Efficiency

In empirical production studies, production functions have been traditionally described as average functions to estimate the mean output rather than the maximum output conditional on the underlying technologies. However, the maximum possible output is relevant in measuring the performance of firms. Farrell (1957) provides a definition of frontier production function which embodies maximality. The frontier is used to measure the efficiency of production units by comparing observed and potential outputs. Potential output is obtained using the best practice technology in the sample from a given vector of inputs.

The literature on the estimation of frontier functions to measure efficiency of producers has been developed in different directions. Different approaches to production, cost and profit frontiers are used to estimate the components of economic efficiency, i.e., technical and allocative efficiencies. Frontier functions can be classified according to the way they are specified and estimated. The classification can be based on the parametric/non-parametric, deterministic/stochastic and cross-section/panel data specifications of the frontier functions. Schmidt (1986), Kumbhakar and Lovell (2000), and Heshmati (2003) present overviews of the concept, modelling, estimation of models and methods to make efficiency comparisons. They also survey some of the empirical applications of frontier functions. This section focuses on the parametric stochastic production frontiers. The stochastic production frontier model for a cross-sectional case introduced by Aigner et al. (1977) is defined as:

(1) $$\ln Y_i = \beta_0 + \sum_j \beta_j \ln X_{jit} + \varepsilon_i , \qquad \varepsilon_i = v_i - u_i$$

where $\ln Y_i$ is logarithm of output of firm *i*, $\ln X$ is a vector of logarithm of J inputs, and β is a vector of unknown parameters to be estimated. The error term ε_i is composed of two components, a symmetric random component $(v_i \neq 0)$, and a one-sided component $(u_i \geq 0)$ representing technical inefficiency. The model can be estimated by corrected ordinary least square, methods of moments, generalised least square or maximum likelihood methods.

Prior to estimation of (1) a number of assumptions are to be made. The random component is assumed to be independently and identically normally distributed, $v_i \sim N(0, \sigma_v^2)$, while the inefficiency component is assumed to be distributed as either exponential, half-normal, truncated normal or gamma. In Battese and Coelli (1995) u_i is obtained by truncation at zero of the $N(\mu_i, \sigma_u^2)$ distribution:

(2) $$\mu_i = \delta_0 + \sum_{j=1} \delta_j Z_{ji}$$

where Z are determinants of inefficiency. The estimated model gives an aggregate fitted value of the two components. Measures of technical inefficiency require decomposition of the error term. Jondrow et al. (1982) have suggested a decomposition method to obtain point estimates of $\hat{u}$ using the mean or mode of the conditional distribution of $E(u_i \mid v_i - u_i)$. Firm-specific rate of technical efficiency, $0 \leq TE_i \leq 1$, is then obtained as:

(3) $$TE_i = \exp(-\hat{u}_i)$$

where the value 1 indicates full technical efficiency in production.

2.2 Productivity Growth

Measurement of productivity is often based on the ratio of some function of outputs (Y_m) and some function of inputs (X_j) where the subscripts *m* and *j* denote types of outputs and inputs. In cases with single or aggregate output, partial or single factor productivity (SFP) are computed as:

(4) $$SFP_j = Y / X_j .$$

SFP can be misleading because productivity is negatively related to the factor intensity and changes in shares of production factors. In order to account for changes in input combinations a total factor productivity (TFP) index is defined as the ratio of (aggregate) output to the weighted sum of production inputs:

(5) $$TFP = Y / \sum_j \alpha_j X_j .$$

The TFP can be measured as changes over time or relative to other firms in a single period. Here the changes are compared to some reference time or firm as:

(6) $$TFP_{t,t-1} = (Y_{it} / X_{it})/(Y_{it-1} / X_{it-1}) \quad \text{and} \quad TFP_{i,j} = (Y_i / X_i)/(Y_j / X_j).$$

The first measure is credited to Tinbergen (1942) and it has been modified by Solow (1956, 1957), Kendrick (1961), and others. The productivity growth, $(T\dot{F}P)$, over two points in time (*0* and *1*) is measured as (see also recent survey by Good, Nadiri and Sickles, 1997):

(7) $$\begin{aligned} T\dot{F}P = \Delta TFP / TFP &= [((Y_1 / Y_0)/(\sum_j w_j X_{j1} / \sum_j w_j X_{j0})) - 1] \\ &= [(Y_1 / Y_0)/(\sum_j \alpha_j (X_{j1} / X_{j0})] \end{aligned}$$

where $\Delta TFP = TFP_{t+1} - TFP_t$ is change in *TFP*, *w* is input price, α_j is the expenditure share for inputs *j* and *0* is the reference time period.

TFP growth can be decomposed into technical change and scale components. Diewert (1981) classified the various measures of technical change into four groups: econometric estimation of production and cost functions, Divisia indices, exact index numbers, and non-parametric methods using linear programming. Here we focus on the first approach, but also discuss the Divisia index and a benchmark. In the econometric approach, technical change has generally been represented by a simple time trend and assuming a flexible functional form (Christensen et al., 1973). Access to panel data allows for general index of technical change (Baltagi and Griffin, 1988)[1], where the time trend is replaced by a vector of time dummies. Let the production function be characterised by:

(8) $$Y = f(X, t)$$

[1] Other applications of the General Index model of technical change is found in Baltagi et al. (1995), Kumbhakar and Heshmati (1996), Kumbhakar et al. (1999) and Kumbhakar et al. (2000).

where Y is output, X is a vector of J input variables, and t is a time trend variable representing technology. Taking the total differential of (5) we get:

$$(9) \qquad \dot{Y} = \sum_j (f_j X_j / Y)\dot{X}_j + (f_t / Y)$$

where a dot indicates growth rate and f_j is the marginal product of the jth input. The relationship can be rewritten as:

$$(10) \qquad \dot{Y} - \sum_j s_j \dot{X}_j = (RTS - 1)\sum_j s_j \dot{X}_j + (f_t / Y)$$

where s_j is the cost share of input j and RTS is returns to scale. The left-hand side is the Divisia index of total factor productivity growth:

$$(11) \qquad T\dot{F}P = \dot{Y} - \sum_j s_j \dot{X}_j$$

where only the growth rates in inputs and outputs and the cost shares are required for the calculation of the TFP growth index. Here constant returns to scale are assumed and TFP growth equals the rate of technical change. However, the TFP growth estimates can be obtained by estimating a production function and allowing for variable returns to scale. The TFP growth rate can be decomposed into technical change (TC), and scale (RTS) components (see Kumbhakar et al., 1999):

$$(12) \qquad TF\dot{P} = TC + (RTS - 1)\sum_j \beta_j \dot{X}_j$$

where β is a vector of input elasticities. A positive (negative) rate of TC in production functions indicates technical progress (regress) which is manifested by a positive (negative) shift in the production function over time.

2.3 Competitive Strategy

The measurement of competitive strategy is important in strategic management. Porter (1980) defined three competitive strategies: cost leadership, differentiation, and focus. Nayyar (1993) empirically identify the appropriate level to measure competitive strategies and to determine whether cost-leadership and differentiation strategies are mutually exclusive. Empirical results are based on responses to a questionnaire containing items to measure competitive strategy on large number of products and businesses. The principal component analysis is used to load together different factors in single strategy factors. Results point to multidimensionality of each competitive strategy. No evidence supporting the existence of combined competitive strategy at the product level is found. Sensitivity analyses suggest that business-level measures are not good indicators of product-level competitive strategies. In addition one should better account for product portfolio heterogeneity held by firms across different businesses.

It was mentioned previously that outsourcing is primarily a search for labour cost saving and an optimal choice between inside and outside production. The top five reasons for outsourcing based on a large survey of companies were identified by Deavers (1997) as: to improve company focus, access to world-class capabilities, to accelerate benefits from reengineering, to share risks and to free resources for other purposes. However, Chen et al. (2004) show that trade liberalization may create incentive for strategic international outsourcing arising from multi-market interactions among firms. Unlike the outsourcing motivated by cost saving, strategic outsourcing can have a collusive effect and raise prices in both the intermediate-good and final-good markets. Quelin and Duhamel (2003) view outsourcing as a choice that lies in the corporate policy, not just a business strategy.

In reviewing the characteristics of outsourcing strategies Gilley and Rasheed (2000) propose two types of generic outsourcing: peripheral and core outsourcing. Regression results from analysing the influence of outsourcing intensity on financial, innovation and stakeholder performance did not support the above hypothesis. Results of a number of large surveys suggest that outsourcing is considered as a corporate competitiveness strategy with major improvement in the performance of the company as outcome not just a search for low wages (see Deavers, 1997). Shy and Stenbacka (2003) offer an analysis of how firms use their design of organizational production mode as a strategic instrument and demonstrate that introducing competition into input-producing industry does not reduce efficiency by not exploiting economies of scale. Sharpe (1997) finds outsourcing as a management tool to address organizational competitiveness in an efficient way by moving towards business strategies based on core competencies and outsourcing other non-core activities and services to external suppliers.

2.4 Outsourcing

Having discussed studies on the link between competitive strategy and outsourcing in the previous section, the focus here is on the link between outsourcing and productivity. Industrial, communication and technological development has resulted in major changes in the ways products and services are produced and distributed. As a measure to improve efficiency, firms allocate their resources to activities for which they enjoy comparative advantage, while other activities are increasingly outsourced to external suppliers. Outsourcing is expected to reduce production cost relative to internal production because outside suppliers benefit from economies of scale, smoother production schedules and centralisation of expertise (Anderson and Weitz, 1986; Williamson 1989; Chalos 1995; and Roodhooft and Warlop, 1999). However, the choice between internal or external production requires other considerations than pure production cost differences. For instance, according to the transaction cost economics, outsourcing is desirable only when the sunk cost of asset specific investments is lower than the production cost advantage. Gavious and Rabinowitz (2003) in determining optimal knowledge outsourcing policy, find that the lower the ability to develop internal knowledge, the more favourable external knowledge becomes.

Outsourcing if often related to production of intermediate goods or hiring temporary labour. According to a two-sector model, during recent decades the service sector has grown much faster than the goods sector with negative impacts on economic growth (Baumol 1967; Baumol et al., 1985). In this model, manufacturing is the progressive and technologically advanced sector, while the service sector is stagnant. The negative effect is due to the high labour intensity in the service sector and its low incentives to introduce technological change. However, technologies specific for the use in the service sector is advancing rapidly eliminating previous productivity gaps.

There are a number of studies that focus on explaining the difference in productivity growth rates in the two sectors. Abraham and Taylor (1996) found that firms contract out services with the objectives of smoothening production cycles, benefiting from specialisation and to realise potential labour cost savings. Siegel and Griliches (1992) for selected services found weak evidence that outsourcing leads to overstatement of manufacturing productivity growth. Ten Raa and Wolff (1996) found a positive association between outsourcing and productivity growth in the goods sector. More recently Fixler and Siegel (1999) focus on the internal generation, the buy or outsourcing decision for selected services, and the effects of outsourcing on manufacturing and productivity growth of services. The decision to outsource is modelled for a manufacturing firm consisting of two separate divisions. One unit produces the output and the other provides support services. A firm will outsource if marginal cost of internal production is higher.

Sharpe (1997) argues that outsourcing arose to reduce the adjustment costs of responding to economic changes. Adjustments were to technological innovation, changing customer preferences, and other shifts in supply and demand. These changes affect the labour market and its functions. It has been argued that outsourcing has resulted in falling wages of the less-skilled workers in relation to the more-skilled US workers, causing wage inequality (Feenstra and Hanson, 1995, 1996 and 1999). However, in a recent study using West German manufacturing industries Falk and Koebel (2000) did not find any strong linkage between outsourcing and wages. The issues of innovation and the wage effects of international outsourcing have been investigated by Glass and Saggi (2001). They find that outsourcing lowers the marginal cost of production, increases profit and creates greater incentives for innovations. Standardisation of production technologies is a main factor that in recent years has contributed to the increasing outsourcing of innovation activities.

2.5 Product and Process Innovation

The link between innovation and performance at the firm level has received great attention in a number of studies. These have resulted in important findings regarding expected effects, the data and methods used, as well as their benefits and limitations. Cohen and Klepper (1996) and Klette and Kortum (2001) present a list of stylized facts on the relationship between firm size, R&D effort, productivity and growth. Empirical findings[2] indicate a positive relationship between R&D activity and the level of productivity.

In a survey of econometric studies of R&D and productivity at the firm level, Mairesse and Sassenou (1991) document widely varying estimates of the contribution of R&D to productivity. The variations are mainly observed across data samples, model specifications

[2] For a selection of recent reviews or studies on the link between innovation and productivity, see Griliches (1992, 1995) Cohen and Klepper (1996), Hall and Mairesse (1995), Crépon, Duguet and Mairesse (1998), Klette and Kortum (2001) and Lööf and Heshmati (2002).

and in relation to the use different estimation methods. Mairesse and Sassenou suggest three improvements to the measurement of R&D productivity impacts. These are: improvement of existing databases and measurement of variables, to gain a better understanding of the diversity of the situations of individual firms and their evolution over time, and to the data-type related puzzling differences in the estimates of R&D elasticity in the productivity equation. Hall and Mairesse (1995) perform sensitivity analysis to identify causes and to quantify the degree of heterogeneity in results. The results suggest that more information on the history of firms' R&D expenditures helps to improve the reliability of the estimates of R&D elasticity.

In an innovation model developed by Crépon et al. (1998), a four equations (investment decision, innovations input, innovations output and productivity growth) knowledge production function model was introduced. The model includes three relationships between: innovation output and productivity, investment in research and innovation output, and the research investment and its determinants. Lööf and Heshmati (2002 and 2006) investigate the sensitivity of the estimated relationship between innovativeness and firm performance in a multidimensional framework. They investigate the sensitivity of results with regards to different types of models, estimation methods, measures of performance, sub-populations of industries, different data sources, and different specifications of innovation. The results suggest presence of heterogeneity in effects in several of the above dimensions.

3. THE INNOVATION SURVEY DATA

The data used here are collected within the framework of the second European Community Innovation Survey (CIS).[3] It is considered as a good proxy of the complicated process which transforms innovation investments into production and growth. The results are based on Swedish CIS data covering 1996-1998. The number of observations is 1694. The variables used in the empirical analysis include: innovation input, innovation output, standard production factor inputs and outputs, productivity and efficiency, and other indicators of firm outsourcing, competitive strategy and production environmental variables. These variables are defined below. A summary statistics of the data and variables is presented in Table 1. If desired, for comparison purposes the final sample of firms can be further divided into a number of sub-samples of: manufacturing, services, innovative (radical, incremental, product and processes) and non-innovative firms.

There is detailed information on innovation investment. Innovative investment by firms is broken down into seven different categories. The traditional measure labeled as internal R&D, corresponds to 1.5% of total sales, while all seven categories together correspond to 3.9% of the total sales. Nearly 62% of all firms made investment in some innovative

[3] The OECD, Eurostat and several other national and international organizations have developed and standardized the methodology and information collected by innovation surveys. Several innovation surveys which are internationally comparable have been completed several by EU and some non-member countries. The questionnaire and methodology in these surveys are based on the Oslo manual (1997). The manual proposes guidelines for the collection and interpretation of innovation data.

activities in 1998. The investment strategy is broadly divided into investment in product and process innovations. Here we use the sum of innovation investment in product and processes as a measure of innovation input.

The product innovation is further divided into five innovations activities related to: opening up of new markets, improved product quality, replacement of phased-out products, extension of the product range, and fulfillment of regulations and standards. The process innovation involves measures aimed at: reducing labor cost, material consumption, environmental damages, and energy consumption, and improving production flexibility. Each of the above strategies is further divided according to moderate and strong degrees of importance. Among the product innovations, extension of the range of products and opening up of new markets are found to be of moderate and strong importance, respectively. In the case of process innovations, improving product flexibility and reducing labor cost exhibit the moderate and strong levels of importance, respectively.

The CIS survey contains several alternative measures of innovation output. We define a firm innovative if it has positive innovation input and positive innovation sales. There are three categories of innovation sales: (i) products technologically new for the firm but not new for the market, partly or totally developed by the firm, and introduced on the market during the recent three-years, (ii) products technologically improved, and (iii) products technologically new both for the firm and for the market. Here we use the sum of the first two categories as incremental measure of innovations, and compare this measure with the third category classified as radical innovations.

Depending on data availability, the performance of firms can be measured in different ways. We have looked at three measures of performance. These measures are growth in turnover, value added and employment. They also show similar growth patterns. However, there is a large difference in mean growth rates between innovator and non-innovator firms, when not controlling for size, capital intensity, human capital, R&D etc.

A number of restrictions are imposed on the final data. First, we have removed all observations for which value added or employment was zero or missing. Second, we excluded any observation for which the growth in value added or labor productivity for 1996-1998 was more than 300%. Finally, observations for which the growth in labor productivity was less than –75% were also excluded. These exclusions eliminated the influence of observations outside the above ranges of expansion and contraction on the estimation results.

Table 1 presents some statistics for the variables included in the CIS data. The CIS data also contains information about the firm's strategy on innovations. The most important objectives of product innovations are the opening up of new markets and improvements product quality. Reducing labor costs and material consumption dominates among the most important objectives of the innovative sample. Customers and sources in the enterprise are the most important sources of knowledge for innovation. Domestic customers and supplier universities are the most common co-operative partners in innovation activities. There exists co-operation between firms on innovation. Domestic co-operation is the dominant form of co-operation. There are several factors that negatively affect innovation. These factors are grouped into: projects delayed, abolished or hampered at the start. Lack of qualified personnel and organizational rigidities were identified as the two most important factors delaying innovation. Presence of risks and the lack of qualified personnel were the most important factors in abolishing innovation projects. High risks and costs dominate the causes of innovation projects not starting at all. Among factors hampering innovation, a delay in projects because of the lack of qualified personnel and organizational rigidities are the most important factors.

4. THE RELATIONSHIP BETWEEN THE VARIABLES

The framework used here is based on a Cobb-Douglas production function[4] explaining variation in firm output by a number of standard input variables and a R&D investment variable. The relation is written as:

(13) $$\ln Q_i = \beta_0 + \sum_j \beta_j \ln X_{ji} + \beta_{RD} \ln R\&D_i + \varepsilon_i$$

where ln denote logarithmic transformation, i indicate firm, Q is output produced, and X is a J vector of standard inputs (such as labor, capital, material and energy). β_j is the elasticity of output with respect to a vector of inputs, β_{RD} is the elasticity of output with respect to changes in R&D, and ε is a random error term.

A limitation of the above relationship is that it only measures the relationship between R&D and output. It neglects a link labeled by Pakes and Griliches (1984) as the knowledge production function defined as production of commercially valuable knowledge or innovation output. In order to overcome the above limitation Pakes and Griliches suggest an alternative production function model corresponding to a three equation relationship including: innovation input, innovation output and productivity equations (see Griliches 1990). In order to correct for undesirable properties of selectivity and simultaneity biases and to account for the complexity of innovation process, Crépon et al. (1998) specified a modified version of the above model consisting of four equations. In the innovation literature the latter model is referred to as the CDM model which in its original notation is written as:

$$g_i^* = x_i^0 b^0 + u_i^0$$
$$k_i^* = x_i^1 b^1 + u_i^1$$
$$t_i^* = \alpha_k k_i^* + x_i^2 b^2 + u_i^2$$
$$q_i = \alpha_t t_i^* + x_i^3 b^3 + u_i^3$$

where g_i^* is expresses investment decision, k_i^* is a latent or true research intensity per employee, t_i^* is expected patent per employee or latent share of innovation sales, and q_i is labor productivity defined as value added per employee. The x variables are vectors of

[4] It is straight forward to use a flexible functional form to allow for variations in elasticities, returns to scale and rate of technical change across firms of different: specializations, sizes, locations and industrial sectors.

explanatory variables. The basic econometric problems addressed in the CDM are selectivity and simultaneity biases. The objective is to consistently estimate the causal effect of innovation investment on innovation output and the causal effect of innovation output on productivity. The first equation is a selectivity equation, modeled as a probit, where the dependent variable is a latent innovation decision variable. The remaining three equations are corresponding to those of Pakes and Griliches model. When only the innovation sample is used in standard regression analysis, selectivity problem may bias the results. Innovation input and innovation output appear as explanatory variables in the innovation output and productivity equations. Because of the endogeneity of these variables, we cannot assume that the explanatory variables and the disturbances are uncorrelated. As a result, an ordinary least square regression applied to the above relation will be biased and inconsistent. To overcome the endogeneity problem, CDM suggest estimation of the above relation using a reduced form of the model. Here we use a simpler multi-step estimation approach and yet account for the same sources of bias.

Here the knowledge production function is generalized to incorporate the effects of competitive strategy, outsourcing and efficiency. The system consists of four equations. The first two equations representing innovativeness and innovation inputs are estimated separately as a generalized tobit model where observations on both innovative and non-innovative firms are included. The last two equations are estimated as a system using three stages least squares (3SLS) method. The second step is limited to innovative sample with strictly positive innovation input and innovation output. The four equation model is written as:

$$IN_i^* = \beta_0^1 + \sum_n \beta_n^1 \ln X_{ni}^1 + \beta_{OUTS1} OUTS1_i + \varepsilon_i^1 \quad (14)$$

$$\ln II_i = \beta_0^2 + \sum_m \beta_m^2 \ln X_{mi}^2 + \varepsilon_i^2 \quad (15)$$

$$\begin{aligned} \ln IO_i = {} & \beta_0^3 + \sum_l \beta_l^3 \ln X_{li}^3 + \beta_{RD} \hat{II}_i + \beta_{MR} \hat{MR}_i + \beta_{EFF} EFF_i + \beta_Q \ln Q_i \\ & + \beta_{COM} COMP_i + \beta_{OUTS2} OUTS2_i + \varepsilon_i^3 \end{aligned} \quad (16)$$

$$\ln Q_i = \beta_0^4 + \sum_j \beta_j^4 \ln X_{ji}^4 + \beta_{IO} IO_i + \beta_{EFF} EFF_i + \beta_{OUTS1} OUTS1_i + \varepsilon_i^4 \quad (17)$$

where IN^* is a latent innovation decision variable, the observable counterpart $IN = 1$ when $IN^* > 0$; i.e. if the firm is engaged in innovation, else zero, $\hat{II}$ represents predicted innovation input, *IO* innovation output, *Q* productivity, and $\hat{MR}$ inverted Mill's ratio introduced to correct for possible selection bias, *X* are explanatory variables including employment, physical capital, human capital and various indicators, *EFF*, *COMP*, *OUTS1* and *OUTS2* are variables representing productive efficiency, competitiveness and outsourcing, respectively, and the $\beta : s$ are unknown parameters to be estimated. The outsourcing measure *OUTS1* is based on hiring temporary labor while *OUTS2* is purchase of external innovation related services.

Starting with the first two equations, β^1 and β^2 are vectors of unknown parameters to be estimated reflecting the impact of certain factors on the probability of being engaged in

R&D and other innovation investments and on the actual level on these investments. The β^3 are estimated parameters associated with the level of innovation output while β^4 are associated with the determinants of productivity growth.

Equations 14 and 15 are estimated jointly in a generalized tobit model. The ε^1 and ε^2 are random error terms with mean zero, constant variances and not correlated with explanatory variables, but correlated with each other. From the generalized tobit model estimates of *II* and *MR*, $\hat{II}$ and $\hat{MR}$, are obtained and used as explanatory variables in equation 16. Equations 16 and 17 are then estimated based on sample with positive innovation input and outputs. One problem here is that some of the explanatory variables are often determined jointly with the dependent ones. For example, the innovation input (*II*) is endogenous in the innovation output equation (16), and innovation output (*IO*) is endogenous in the productivity equation (17). In order to derive a consistent estimator, we account for simultaneity by relying on the instrumental variable approach. The instruments consist of variables not correlated with the model error terms but correlated with the endogenous variables. The instruments are described below in Section 5 as x^3 and x^4 vectors.

It should be noted that, in addition to the simplification of the estimation procedure, splitting the four equations into two parts, not only allows for within-part correlation but also for limited between-part correlation among the error terms facilitated through inclusion of the *MR* in the second part. Our approach is thus an intermediate approach compared to the Pakes and Griliches (1984) model which neglects correlations and the Crépon et al. (1998) approach allowing for full correlation among the four equations.

5. SPECIFICATION OF THE MODEL

In using cross-sectional data in the context of innovation, we observe R&D or innovation investment only for a single year. We must therefore assume that the level of investments in year *t* can be used as a proxy for long-term R&D investment. This presumes that firms do not experience major fluctuations in their R&D investments behavior. There is evidence that R&D expenditures are highly correlated from one year to another (Griliches, 1988).

The dependent variables include log innovation input per employee, *II* in equation (15), log innovation sales per employee, *IO* in equation (16) and log productivity, *Q* in equation (17). Productivity growth can be defined in different ways based on total value added, turnover, employment or profit, and expressed in levels or growth rates. Here it is measured as the growth rate in respective variables between 1996 and 1998, i.e. $\log(Q_{it}) - \log(Q_{i,t-1})$, where *t* and *t-1* indicate 1998 and 1996, respectively.

The determinants of innovation input labeled as the x^1 vector consist of growth in employment, profitability, capital stock intensity, capital and knowledge intensive technologies, firm size and industrial sector dummy variables. The profitability and capital stock intensity variables are measured in per employee and expressed in logarithmic forms.

The x^2 variables in the selection equation consist of hired temporary supply labor, profitability, capital investment intensity, indebtedness, export share of turnover, capital and knowledge intensive technologies, firm size classes and industrial sectors dummy variables. The investment intensity and profitability are expressed per employee and are measured in logarithmic forms. The size variables divided into 3 size classes are based on the number of employees. The reference groups include the small size and industrial sector number 1.

The determinants of innovation output labeled as the x^3 vector consist of predicted value of innovation input, estimated inverted Mill's ratio, predicted value of firm performance, logarithm of R&D intensity, growth in employment, purchase of innovation related outsourcing services, efficiency in production, firm size and industrial sector dummy variables. The predicted innovation input and Mill's ratio variables are based on results obtained from the first two equations. In addition the set of variables include a number of composite indices obtained by using principal component analysis. These include indices of hampered project and hampering factors, sources of product and process innovations, competitive strategy, and the importance of innovation cooperation and location of innovation cooperation partners.

The x^4 vector entering the productivity equation contains information on predicted value of innovation output, the temporary hired share of labor, efficiency in production, R&D intensity, capital investment intensity, capital stock intensity, profitability, indebtedness, size and industrial sector dummy variables. The R&D, profitability, investment and capital intensity variables are expressed in logarithmic forms. The predicted value of innovation output and performance are obtained from estimation of single equations specified as in above.

6. EMPIRICAL RESULTS

Empirical results in this paper are based on the Swedish innovation survey data described earlier. The data is cross-sectional covering 1998 and expanded with additional information on employment and output in 1996. The total number of observations used in the estimation steps is 1694. A number of economic variables used in the regression analysis are obtained from balance sheet of the firms from register data. A complete summary of data is given in Table 1. This section contains discussion of specification tests and estimation of the models and detailed analysis of the results.

6.1 Specification tests

A number of models and estimation methods are involved in generation of the results. For the efficiency scores we specify a frontier production function estimated using maximum likelihood method (Battese and Coelli, 1995). The production function where the dependent variable is defined as value added is specified in terms of capital and labor inputs. In addition we control for heterogeneity of firms by including dummy variables indicating which sector the firms belong to and their sizes based on the number of employees.

Furthermore a number of determinants of inefficiency are incorporated to explain variations in inefficiency among the sample firms. Likelihood ratio tests indicate presence of inefficiency in production and that the determinants of inefficiency should be included in the efficiency effects model specification.

We have used two different (labor-specific and general) measures of outsourcing to study the effects of outsourcing on efficiency in production, innovativeness, innovation outputs and productivity growth of firms. However, due to lack of detailed information about firm-level characteristics we avoided to identify determinants of outsourcing and to model outsourcing decisions of firms.

For the specification of the innovative model estimated by maximum likelihood method, availability of data and the relationship between explanatory variables and their expected relationship to the decision of innovation investment, as well as individual variables significance level determined the final model specification. Here instead of a Heckman two-step procedure[5] we used a generalized tobit model with selection effect.

The remaining models of innovation output and productivity growth are estimated jointly as a system using three-stage-least-square estimation method. The sample is restricted to only innovative firms but it accounts for selection effects. Many of the innovation activities, obstacles, co-operations and strategy indicators were formulated as complex questions in the questionnaires. In order to avoid large number of dummy variables we estimated a number of composite indices using principal component analysis (see Table 2). These composite indices are then used in the final stage of the model as determinants of innovation and performance of firms.

6.2 Efficiency results

The parameters of the frontier production function estimated using maximum likelihood method are given in Table 3. In the estimation we control for heterogeneity of firms by controlling for the industrial sector that firms belong to. In addition a number of determinants of inefficiency are identified and their impacts on firms' efficiency quantified. The first two coefficients are elasticity of output with respect to capital and labor inputs. The labor elasticity is much higher (0.88) than the capital elasticity (0.10). They are significantly different from zero and sum up to 0.98, interpreted as decreasing returns to scale, but statistically not different from constant returns to scale. Four of the six sector dummy coefficients are statistically different from zero indicating presence of significant industrial sector heterogeneity in the data.

There is a negative relationship, and at an increasing rate, between inefficiency in production and size of firm. Profitability and investment intensity per employee, outsourcing defined as share of temporary hired labor and R&D investment intensity enhances efficiency in production. We expected that high level of indebtedness and export orientation to increase efficiency in production, but these were statistically insignificant.

[5] The two steps consist of a probit model in the first step to estimate the decision of innovation investment and a standard regression model of determinants of level of innovation investment in the second step.

Industries with capital, knowledge and labor intensive production technologies are found to be technically less effective than industries with average production factor intensity.

The mean technical efficiency is 0.834 indicating that on the average, there is potential that for given level of capital and labor the firms could produce 16.4% more output by using the best practice production technology. Efficiency in production is positively correlated with innovations input, innovations output, productivity growth and temporarily hired labor. There is significant difference in efficiency levels by industrial sector. Industrial sectors 1-3 are much less effective than industrial sectors 4-7. Larger firms and firms with radical innovation are more efficient than small and less innovative firms. The higher efficiency of firms with average input factor intensity is indication of complementarity of capital, knowledge and labor inputs in production.

6.3 Productivity results

Since we have no access to cross-section of time-series data, it was not possible to decompose the total factor productivity growth based on the frontier production function into its underlying technical change and scale components. Furthermore, the returns to scale obtained from the estimation of a production function was found to not deviate from a constant returns to scale. Therefore, we used the growth rate in turnover and value added during 1996-1998 to proxy productivity growth. Although, the latter based on the register data is found to be more reliable then the former obtained from the survey data. The regression analysis is based on value added definition of growth. The different growth variables by various characteristics are computed and briefly described below.[6]

Growth in employment varies by industrial sector. Employment did not grow in sectors 1 and 4, while in sectors 3 and 5-7 it grew by 20-22% during 1996-1998. The corresponding growth in capital was in the interval 16% to 36%. Growth rates in turnover and value added differ somewhat but the patterns are similar among the industrial sectors. Growth in value added is higher in general and it is the highest among sectors 3 and 5-7. The medium-sized firms followed by large firms experienced much higher growth in turnover and value added than small firms. Productivity growth is much higher for the knowledge intensive firms compared with capital and labor intensive firms, but the rate of productivity growth is the highest amongst firms with average factor intensity. Productivity growth is positively related to innovativeness, innovation output, outsourcing (temporary hired skilled labor), and efficiency in production, but negatively correlated with innovation input.

6.4 Competitiveness results

Principal component analysis (PC) is used to compute composite competitiveness indices. Given a dataset with *p* numeric variables, at most *p* principal components can be computed;

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[6] The results related to summary of different indicators by various firm characteristics and their correlation discussed in the subsections 6.4 to 6.6 are not reported here due to limited spaces. These are available from the author upon request.

each is a linear combination of the original variables. PC analysis can be viewed as a way to uncover approximate linear dependencies among variables.[7]

The competitiveness index indicates the level and state of competitiveness among firms. If necessary the index can be broken down into different underlying components. A breakdown of the index into major components provides possibilities to identify key sources of competitiveness. The breakdown of the index can be based on canonical correlation looking at the correlation relationship between two or more sets of variables. The indices can be used to study the causal relationship between competitive strategy, innovativeness, efficiency and productivity growth at the firm level.

The competitiveness strategy index in this study is constructed based a question on the importance of 10 different factors on competitiveness of firms products and processes. These include: prices, quality, production flexibility, delivery, originality, brand value, design, uniqueness, knowledge intensity, and other factors. The scale of importance is: very important, important, less important, and not relevant. Using the combination of the 10 factors and 4 scales, a composite competitiveness strategy index was created. The resulting index based on the first principal component is reported on Table 2.

Due to the way the scale of importance is numbered, the higher the index the less important is the strategic importance of the factors. Strategy is thus negatively correlated with hampered project and positively correlated with hampering factors, sources of product and process innovation, their importance and location. The sectors differ by strategy. The index level is an increasing function of the size of firm. It is highest for capital and knowledge intensive and innovative firms.[8]

6.5 Outsourcing results

For the estimations we have used two measures of outsourcing. One is based on hired labor defined as the ratio of temporary hired labor to the total labor force in1998, labeled as *OUTS1*. A second measure is based on the expenditure to develop new or significantly improved product and processes in 1998, labeled as *OUTS2*. It is measured as the sum of expenditures associated with the purchase of external R&D services, including acquisition of machinery, knowledge, training and market introduction of innovations.

The average share of temporary hired employee is 1.3%, while the expenditure share of outsourcing is 23.9%, with larger relative dispersion in the former. The two measures are correlated at a very low rate, only 0.068. The hired labor measure is positively correlated with innovation output and growth in value added and efficiency, while the expenditure measure is positively correlated with both innovations input and output but not with growth in value added or efficiency in production.

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[7] This method gives a least square solution by minimizing the sum of all the squared residuals, measured as distances from the point to the first principal axis. In the ordinary least squares case the vertical distance to the fitted line is minimized.

[8] The correlation matrix is not reported here.

The industries differ by degree of outsourcing. As mentioned earlier, outsourcing of products, services and processes is more intensive than hiring labor on temporarily basis. The expenditure share of outsourcing is an increasing function of the size of firm. Large firms outsource 33.4% of total expenditure for their innovation activities. The corresponding share for small firms is only 19.1%. Knowledge intensive firms' share of outsourcing is highest among sample firms. Outsourcing is also found to be positively associated with the degree of innovativeness.

6.6 Other composite innovation indices

In addition to the competitiveness strategy index described above six other composite indices are computed using the principal component analysis. These are: sources of product innovations, sources of process innovations, factors hampering innovation, hampered innovation projects, importance of innovation co-operation partners, and geographic location of co-operation partners. The questionnaire was constructed such that high values of the indices have negative relationship to performance of firms. The results from PC analysis together with a summary of the indices are found on Table 2.

Only in two cases, factors hampering innovation (0.431) and location of co-operation partners (0.266), the eigenvalues of the first three principal components is greater than 1. However, in those two cases the share of variance explained (in parentheses) is relatively low. In the remaining five index cases, only the first principal component eigenvalue is exceeding 1. The share of the variance explained in ascending order are: factors hampering innovation projects (0.600), strategy of innovation (0.721), importance of co-operation (0.857), sources of product innovation (0.883), sources of process innovation (0.983).

All indices are normalized to mean zero and variance 1. The range and distribution of the individual indices vary among the indices. The sources of variations depend on the underlying variables. Location of innovations partners followed by hampering factors indicates the highest variations, while sources of product and process innovations the lowest.

Correlation coefficients among the composite indices are computed. A high value of the hampered project index which indicates success of the project is negatively correlated with hampering factors, where a higher value of index indicates strength of the negative factors. The hampered projects index is negatively correlated with remaining indices but the size of correlation coefficients are small. The sources of product and process innovations are positively correlated among themselves and with all other indices, hampered projects being excepted. The strategy index is highly correlated (0.75) with sources of product innovation. The importance of co-operation partners and their location are positively correlated (0.51). Co-operation on innovation with different partners is important for strategy and success of innovation activities. The same is true with location of partners but at lower rate of importance. The sources of product innovations index is highly correlated with strategy of innovation and importance of co-operation partners (0.56). The latter two are also highly correlated (0.58) and might, cause problems to separate their effects.

In looking at the mean composite indices by firm characteristics, we find that the industrial sectors differ by index levels. The largest values are in almost all index cases associated with sector 6 and the lowest to sector 2. There is a clear pattern in the relationship between the level of the indices and the size of firms. With the exception of hampering factor the indices are a positive function of the size of firms. Firms with capital and labor intensive production technologies show much higher index levels than those with labor or average factor intensity in production. The same positive relationships holds for firms with radical and incremental innovations compared to those with no innovation.

6.7 The generalized knowledge production function results

In this section we present the results from the empirical analysis of the causal relationship between knowledge capital and performance indicators at the firm level where the model is generalized to account for firm strategy and outsourcing activities. Up-to-date econometrics techniques accounting for selection and simultaneity biases are applied to Swedish innovation survey data. The results support a positive relationship between investment in innovation and productivity growth at the firm level.

The decisions to make investment in innovation and how much to invest are estimated jointly in a generalized tobit model with selection effects by maximum likelihood method (see Table 4). Using the parameter estimates the Mill's ratio correcting for the effects of sample selection bias and predicted innovation input are computed and introduced as explanatory variables in the innovation output equation. The innovation output equation is then jointly estimated together with productivity equation using three stages least squares estimation method (see Table 5). The estimation is based on sample of innovative firms. A firm is classified as innovative if both innovation input and innovation outputs are positive. A total of 871 firms or 51.4% of the sample of 1694 firms are classified as innovative.

Innovation investment equation

The LR test of independence of the two equations containing the generalized tobit model does not reject the null hypothesis $(H_0 : \rho = 0)$, suggesting that it is not necessary that the two equations are estimated jointly. The coefficient associated with selection is also insignificant indicating no selection on firms that are very likely to be engaged in innovation activities. The estimation results from the two equations are presented on Table 4. In order to identify the parameters of interest, the two equations differ in specification by a number of variables including outsourcing, growth in employment, investment and capital stock intensity and export shares.

The estimation results show that profitability is a major determinant of innovation investment indicating the importance of internal financial sources. Knowledge intensity and size of firm are two other factors affecting positively a decision of investment in innovation. Growth in employment, capital intensive production technology and capital investment were found to be insignificant. Sector 4 and 6 have lower propensity than sector 1 to invest in innovation.

We expected increased outsourcing defined as the share of temporary hired labor to enhance investment in innovation. However, this variable was found to be insignificant. Profitability affects the decision to invest but not as much the level of investment. Indebtedness also turned out statistically insignificant. The large firms probably do not have significant liquidity constraints. They are indifferent in their choices between internal and external sources of finance and have the possibility to combine the two sources. General investment intensity, export share and capital and knowledge intensive production technologies affect positively the level of investment in innovation activities. The level of investment in innovations is a positive and increasing function of the size of the firms. Industrial sector 5 and 7 differ in investment level from the reference sector 1.

Innovation output equation

The 3SLS estimation results from the system of innovation output and productivity equations are reported in Table 5. The coefficient of Mill's ratio is insignificant indicating that selectivity is not being a major problem. However, an insignificant Mills' ratio coefficient should not preclude the first step of the estimation procedure and prediction of innovation input to be used in the innovation output as an explanatory variable.

The model performance measured as R^2 for the innovation output equation is 0.42. Innovation output depends largely on the innovations input. The estimation results from innovation output equation indicates that a 1% increase in investment in innovative activities per employee increases the innovation sales by nearly 0.57%. The feedback effect on innovation output from the productivity growth is positive and statistically highly significant. R&D investment intensity affects positively innovation output. Unlike the sources of product innovation, the sources of process innovation have positive impact on the innovation output. Competitive strategy factors are found to be important for the innovation sales. The level of innovation sales is increasing function of the size of firms. Surprisingly, the hampered projects, hampering factors, growth in employment, importance of co-operation and co-operators location did not turn out to have significant effects on innovation sales. The coefficient of efficiency in production in the innovation sales equation is negative and weakly significant, which is unexpected.

Productivity growth equation

The resulting coefficient of determination (R^2) is 0.19. Most of the selected determinants are found to be significantly different from zero. The coefficient of the key variable – predicted innovation output is positive. The positive and significant coefficients of productivity and innovation output equations indicate presence of two-way positive causal relationship between the innovation output and productivity growth among the innovative firms and that the two equations must be estimated as a system. Production efficiency, investment intensity and indebtedness increase productivity, while R&D intensity, capital intensity, and size decrease productivity growth. The latter is consistent with empirical evidence regarding the relationship between growth and size (Jovanovic 1982). In similarity with innovation output, the degree of heterogeneity in productivity growth by industrial sector is much lower compared to the case of innovation input.

Previous empirical results based on CIS data suggest that the results are sensitive with respect to: the measurement of the dependent variables, industrial sector, estimation methods, data sources, sample of firms and degrees of innovation (see Lööf and Heshmati, 2006).

7. SUMMARY AND CONCLUSIONS

In this paper we introduced a generalization of the knowledge production function by incorporating the effects of competitive strategy, outsourcing and efficiency. We have summarized the methods used and empirical results obtained from studies of the link between corporate competitive strategy, efficiency, outsourcing, innovation and productivity growth at the firm level. After identification of limitations of previously used methods, the new methods are then discussed with a view of dealing with the issues of sample selection and simultaneity biases in innovation studies. Finally, the new econometrics method is applied to Swedish firm level innovation data.

The empirical results from estimation of a stochastic frontier production function suggest that such function is an adequate representation of production relationship. Firms are found to be relatively efficient, although the output can be increased by using the best practice technology. Efficiency in production is positively correlated with innovation input, innovation output and productivity growth. Industrial sectors are heterogeneous in efficiency patterns. The return to scale is close to constant returns to scale indicating on the average presence of optimal scale in production. There is positive association between size of firm, profitability, investment, outsourcing and efficiency in production.

Due to the cross-sectional nature of the data and constant returns to scale it was not possible to estimate the rate of technical change and total factor productivity growth. However, simple growth rates in employment, turnover and value added was computed. The growth in employment, turnover and value added differ in levels and the pattern is heterogeneous by industrial sectors, size of firms and innovativeness. Growth in value added is positively correlated with innovation output, outsourcing, and efficiency in production. Outsourcing share of innovation expenditure is higher than the temporary hired share of labor. The two outsourcing variables differ by size of firm, factor intensity and innovativeness.

It is rather difficult to represent corporate competitiveness strategy in a proper and simple way. The competitive strategy variables have a quite complicated structure causing severe multicollinearity problem. A simple composite competitive strategy index was estimated using principal component analysis. It indicates the level and state of competitiveness among the firms. In addition six other composite indices including factors hampering innovation, hampered innovation projects, sources of product and process innovations, importance and location of co-operation partners in innovation. A composite index is to be preferred to sets of dummy variables in regression analysis. However, a single index has the disadvantage of mixing the individual factor effects. The composite indices are used to test for their effects on firm’s innovation and growth.

We have identified a number of determinants of decisions of investment in innovation activities, how much to invest, innovation output and productivity growth. The systems of four equations were estimated in a muti-step estimation procedure using a combination of generalized tobit and simultaneous equation systems accounting for both sample selection and simultaneity biases. The results suggest that the approach used is appropriate for such case study. Internal financial sources, knowledge intensive production technology and size of firms are major determinants of investment in innovations. Industrial sector are different in their propensity to invest in innovation. General investment intensity, export share and capital and knowledge intensive technologies, and size of firms affect positively the level of investment in innovation.

Variation in innovation output is to a large extent explained by variations in innovation input. The feedback effect from productivity growth on innovation output is also found to be positive. R&D intensity, sources of innovation, competitive strategy and the size of firm have positive impacts on innovation output. Production efficiency has a negative but weakly significant effect on innovation output. The interactive positive and significant coefficients of innovation output and productivity equations indicate presence of a two-way causality relationship between innovation output and productivity growth among innovative firms. Production efficiency, investment intensity and indebtedness increase productivity growth, while R&D intensity, capital intensity, and firm size decrease productivity growth.

The above results are however sensitive to the choice of measures of dependent variables, estimation methods and degree of innovativeness. The data, despite of its limitation in some respects, is rich in information on organization, strategy and innovation activities. These together with the use of advanced estimation method accounting for both simultaneity and sample selection bias are indications of relatively a successful empirical illustration of the relationship between the key variables in a generalized knowledge production function.

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Table 1. Summary statistics of the merged CIS and register data sets, N=1694 observations.

Variable	Definition	Mean	Std Dev	Minimum	Maximum
A. Basic level variables					
ANST9831	employees CIS 981231	130.445	217.499	20.000	1857.000
ANST9631	employees CIS 961231	128.035	224.955	20.000	2110.000
AntAnst	no of employees register	130.759	226.521	20.000	2870.000
OMS98	turnover 1998	232649.601	515673.729	7721.000	8335900.000
OMS96	turnover 1996	208410.415	494618.103	5922.000	10237400.000
fvarde98	value added 1998	74742.996	160602.962	4772.000	2173271.000
fvarde96	value added 1996	65334.751	147080.140	3000.000	2237378.000
EXPORT98	export value 1998	75935.354	293438.030	0.000	4808539.000
EXPORT96	export value 1996	65584.067	258037.777	0.000	3596703.000
capital	material assets	82295.672	408368.915	4.000	8298362.000
B. Dependent variables					
gomsat	growth in turnover	17.514	34.292	-65.002	279.607
gfvarde	growth in value added	22.073	41.040	-68.736	295.437
innovative	share of innovative firms	0.616	0.486	0.000	1.000
innovinput	innovation input	6251.059	35516.832	0.000	999999.000
innovoutput	innovation output	35896.454	140246.679	0.000	2880000.000
C. Explanatory variables					
producty	labour productivity	1677.524	1686.935	200.215	17324.125
profit	profitability/employ	42.733	122.508	-654.881	2283.243
kapstocint	capital stock intensity	554.569	1782.830	0.071	39008.160
kapflowint	capital flow intensity	101.458	257.479	0.000	6493.086
fouint	R&D intensity	9.212	40.769	0.000	670.968
deratio	debt/equity ratio	61.483	21.535	-42.591	138.591
capintens	capital intensive technology	0.071	0.257	0.000	1.000
knointens	knowledge intensive	0.305	0.461	0.000	1.000
labintens	labor intensive	0.286	0.452	0.000	1.000
othintens	others intensive	0.338	0.473	0.000	1.000
manufact	manufacturing sector	0.664	0.472	0.000	1.000
service	service sector	0.280	0.449	0.000	1.000
prodinnov	product innovation	0.507	0.500	0.000	1.000
procinnov	process innovation	0.279	0.449	0.000	1.000
radical	radical innovation	0.507	0.500	0.000	1.000
increment	incremental innovation	0.279	0.449	0.000	1.000
otherm	others innovation	0.441	0.497	0.000	1.000
size	size of firm	1.655	0.678	1.000	3.000
expshare	export share of value added	0.779	1.904	0.000	57.017
gemploy	growth in employment	8.608	27.726	-74.359	285.714
gcapital	growth in capital	21.406	57.896	-99.747	299.277
gexport	growth in export	46.847	340.292	-100.000	8010.204
outsource1	outsourcing hired employee	1.277	6.204	0.000	136.674
outsource2	outsourcing expend. Share	23.911	33.348	0.000	99.000
D. Various composite indices					
efficiency	technical efficiency	0.834	0.146	0.537	1.000
strategy	PC index strategy innovation	-0.000	1.000	-1.287	2.135
hamper1	PC index hampered project	-0.000	1.000	-6.675	0.501
hamper2	PC index hampering factors	-0.000	1.000	-0.456	7.705
sourceprod	PC index sources prod.innov.	-0.000	1.000	-1.188	1.373
sourceproc	PC index sources proc.innov.	0.000	1.000	-0.811	1.444
importance	PC index importance of coop	0.000	1.000	-0.900	1.697
location	PC index location of coop	0.000	1.000	-0.562	11.455

Table 2. Results of principal component analysis, based on 1694 observations.

	Eigenvalue	Difference	Proportion	Cumulative
Eigenvalues of the Correlation Matrix				
1. Strategy of innovation index:				
Prin1	6.4851	5.8436	0.7206	0.7206
Prin2	0.6414	0.2509	0.0713	0.7918
Prin3	0.3905		0.0434	0.8352
Summary	-0.0000	1.0000	-1.2870	2.1350
2. Sources of product innovation index:				
Prin1	12.3648	12.0627	0.8832	0.8832
Prin2	0.3021	0.0045	0.0216	0.9048
Prin3	0.2975		0.0213	0.9260
Summary	-0.0000	1.0000	-1.1880	1.3730
3. Sources of process innovation index:				
Prin1	13.7644	13.7232	0.9832	0.9832
Prin2	0.0411	0.0093	0.0029	0.9861
Prin3	0.0318		0.0023	0.9884
Summary	0.0000	1.0000	-0.8110	1.4440
4. Factors hampering innovation projects index:				
Prin1	1.8008	1.1490	0.6003	0.6003
Prin2	0.6517	0.1044	0.2173	0.8175
Prin3	0.5473		0.1825	1.0000
Summary	-0.0000	1.0000	-6.6750	0.5010
5. Factors hampering innovation index:				
Prin1	2.3846	1.0818	0.2168	0.2168
Prin2	1.3028	0.2500	0.1184	0.3352
Prin3	1.0527		0.0957	0.4309
Summary	-0.0000	1.0000	-0.4560	7.7050
6. Importance of cooperation index:				
Prin1	7.7157	7.3549	0.8573	0.8573
Prin2	0.3607	0.0788	0.0401	0.8974
Prin3	0.2819		0.0313	0.9287
Summary	0.0000	1.0000	-0.9000	1.6970
7. Location of cooperation index:				
Prin1	8.9216	4.9553	0.1439	0.1439
Prin2	3.9662	0.3583	0.0640	0.2079
Prin3	3.6078		0.0582	0.2661
Summary	0.0000	1.0000	-0.5620	11.4550

Notes: Prin1, Prin2 and Prin3 are the first, second and the third principal components.
The columns of summary contains: mean, standard deviation, minimum and maximum values.
The principal component procedure in SAS is used for estimation of these composite indices.

Table 3. Maximum likelihood parameter estimates of the frontier production function.

parameters	coefficient	standard-error	t-ratio
A. Production function part			
Constant	5.8637	0.1237	47.3784
log capital	0.1025	0.0078	13.1160
log labor	0.8800	0.0294	67.9984
sni2	0.0811	0.0335	2.4213
sni3	0.0706	0.0396	1.7837
sni4	0.2742	0.0566	4.8404
sni5	0.0799	0.0751	1.0647
sni6	-0.2623	0.0671	-3.9054
sni7	0.0241	0.0650	0.3716
B. Efficiency effects part			
medium size	-0.0160	0.0130	-1.2330
large size	-0.1064	0.0179	-5.9164
investment intensity	-0.0233	0.0040	-5.7274
profitability	-0.0679	0.0066	-10.1560
debt equity ratio	0.0002	0.0004	0.5858
outsourcing labor	-0.0043	0.0010	-4.1723
export share	0.0033	0.0051	0.6389
R&D intensity	-0.0455	0.0050	-9.0423
capital intensive firms	0.5157	0.0622	8.2883
knowledge intensive firms	0.5416	0.0500	10.8134
labor intensive firms	0.6017	0.0575	10.4610
sigma-squared	0.0920	0.0034	26.9235
gamma	0.0362	0.0054	6.6574
log likelihood function		-357.4846	
LR-test of the one-sided error		380.2175	
number of iterations		53	
number of cross-sections		1694	
mean efficiency		0.8335	

Notes: For definitions of the variables see Table 1. FRONT41 is used for the estimation.
Sigma-square and gamma are reparametrization of the two variance components,
$\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / (\sigma_v^2 + \sigma_u^2)$.

Table 4. Generalized tobit model estimation of innovativeness and innovation input.

Variable	Coef.	Std. Err.	z	P|z|	[95% Conf.	Interval]
A. Innovation decision equation (equation 14):						
constant	-0.4175	0.1967	-2.12	0.034	-0.8029	-0.0320
growth in employment	0.0018	0.0012	1.49	0.136	-0.0005	0.0040
log profitability	0.0333	0.0164	2.03	0.042	0.0011	0.0654
log capital intensity	0.0340	0.0300	1.13	0.257	-0.0248	0.0928
capital intensive technology	0.1560	0.1407	1.11	0.268	-0.1197	0.4317
knowledge intensive technology	0.2385	0.0908	2.63	0.009	0.0605	0.4163
medium size	0.2302	0.0670	3.44	0.001	0.0989	0.3614
large size	0.6518	0.1088	5.99	0.000	0.4385	0.8650
sni2	-0.0839	0.1285	-0.65	0.514	-0.3358	0.1680
sni3	0.2435	0.1521	1.60	0.109	-0.0545	0.5415
sni4	-0.5465	0.1898	-2.88	0.004	-0.9185	-0.1744
sni5	0.1390	0.1832	0.76	0.448	-0.2200	0.4979
sni6	-0.6366	0.1491	-4.27	0.000	-0.9288	-0.3443
sni7	0.1575	0.1492	1.06	0.291	-0.1348	0.4498
B. Innovation input equation (equation 15):						
constant	4.8560	0.4944	9.82	0.000	3.8869	5.8249
Outsourcing (hired employees)	0.0026	0.0075	0.34	0.732	-0.0121	0.0173
log profitability	0.0367	0.0323	1.14	0.256	-0.0266	0.1000
log investment intensity	0.1893	0.0466	4.06	0.000	0.0980	0.2806
debt equity ratio	0.0035	0.0030	1.16	0.247	-0.0024	0.0093
export share	0.1024	0.0227	4.52	0.000	0.0579	0.1468
capital intensive technology	0.4206	0.2360	1.78	0.075	-0.0420	0.8831
knowledge intensive technology	0.5051	0.1597	3.16	0.002	0.1922	0.8180
medium size	0.9528	0.1276	7.47	0.000	0.7028	1.2028
large size	2.4217	0.2061	11.75	0.000	2.0176	2.8256
sni2	0.3506	0.2244	1.56	0.118	-0.0891	0.7905
sni3	0.3390	0.2541	1.33	0.182	-0.1589	0.8370
sni4	-0.1227	0.3597	-0.34	0.733	-0.8277	0.5823
sni5	0.6593	0.3036	2.17	0.030	0.0642	1.2544
sni6	0.1236	0.3325	0.37	0.710	-0.5280	0.7753
sni7	1.0050	0.2429	4.14	0.000	0.5289	1.4811
athrho	0.1802	0.2277	0.79	0.429	-0.2660	0.6263
lnsigma	0.4460	0.0341	13.07	0.000	0.3790	0.5128
rho	0.1782	0.2204			-0.2599	0.5555
sigma	1.5620	0.0533			1.4609	1.6701
lambda	0.2784	0.3511			-0.4097	0.9666

LR test of indep. eqns. (rho = 0): chi2(1) = 0.39 Prob chi2 = 0.5338

Heckman selection model	Number of obs	= 1694
(regression model with sample selection)	Censored obs	= 823
	Uncensored obs	= 871
	Wald chi2(15)	= 230.5100
Log likelihood = -2716.6540	Prob chi2	= 0.0000

Notes: For definitions of the variables see Table 1. Stata is used for the estimation.

Table 5. 3SLS estimation of the innovation output and productivity growth equations.

Variable	Coef.	Robust Std. Err.	t	P|t|	[95% Conf.	Interval]
A. Innovation output equation (equation 16):						
constant	6.5162	2.3779	2.74	0.006	1.8490	11.1834
predicted productivity growth	2.6549	0.9195	2.89	0.004	0.8501	4.4596
predicted innovation input	0.5577	0.2193	2.54	0.011	0.1272	0.9880
mills ratio	-0.3203	1.1431	-0.28	0.779	-2.5640	1.9234
log R6D intensity	0.1275	0.0507	2.51	0.012	0.0278	0.2271
growth in employment	-0.0088	0.0056	-1.57	0.117	-0.0198	0.0022
outsourcing(expenditure share)	0.0007	0.0013	0.54	0.591	-0.0019	0.0033
technical efficiency	-1.4328	0.8516	-1.68	0.093	-3.1042	0.2386
hampered project	-0.0307	0.0618	-0.50	0.619	-0.1519	0.0905
hampering factors	0.0802	0.0515	1.56	0.120	-0.0209	0.1813
sources of product innovation	0.0611	0.1054	0.58	0.562	-0.1457	0.2679
sources of process innovation	0.1408	0.0504	2.79	0.005	0.0418	0.2397
competitiveness strategy	-0.2805	0.0968	-2.90	0.004	-0.4704	-0.0904
importance of cooperation	-0.0032	0.0585	-0.05	0.957	-0.1180	0.1117
location of cooperation	0.0788	0.0501	1.57	0.116	-0.0195	0.1772
medium size	0.3625	0.1928	1.88	0.060	-0.0159	0.7408
large size	0.9770	0.4506	2.17	0.030	0.0924	1.8614
sni2	-0.4534	0.1986	-2.28	0.023	-0.8431	-0.0637
sni3	-0.2971	0.2669	-1.11	0.266	-0.8209	0.2268
sni4	-0.0543	0.5838	-0.09	0.926	-1.2001	1.0916
sni5	0.8804	0.3309	2.66	0.008	0.2309	1.5298
sni6	0.5060	0.7554	0.67	0.503	-0.9765	1.9886
sni7	-0.3141	0.3066	-1.02	0.306	-0.9157	0.2876

B. Productivity growth equation (equation 17):

Variable	Coef.	Robust Std. Err.	t	P|t|	[95% Conf.	Interval]
constant	-1.3846	0.3402	-4.07	0.000	-2.0522	-0.7169
predicted innovation output	0.1146	0.0384	2.99	0.003	0.0393	0.1899
outsourcing(share of employee)	-0.0013	0.0022	-0.57	0.566	-0.0056	0.0030
technical efficiency	0.6434	0.2375	2.71	0.007	0.1772	1.1095
log R&D intensity	-0.0536	0.0115	-4.66	0.000	-0.0762	-0.0309
log innovation intensity	0.0363	0.0132	2.75	0.006	0.0104	0.0622
log capital intensity	-0.0493	0.0168	-2.94	0.003	-0.0821	-0.0163
log profitability	0.0020	0.0124	0.16	0.875	-0.0224	0.0263
debt equity ratio	0.0021	0.0008	2.74	0.006	0.0005	0.0035
medium size	-0.0387	0.0490	-0.79	0.430	-0.1348	0.0574
large size	-0.2918	0.1071	-2.73	0.007	-0.5019	-0.0816
sni2	0.0407	0.0350	1.16	0.245	-0.0280	0.1094
sni3	0.0320	0.0423	0.76	0.450	-0.0511	0.1150
sni4	-0.0680	0.0809	-0.84	0.400	-0.2267	0.0906
sni5	-0.2246	0.0955	-2.35	0.019	-0.4120	-0.0370
sni6	-0.1274	0.0930	-1.37	0.171	-0.3100	0.0551
sni7	-0.0653	0.0823	-0.79	0.428	-0.2268	0.0961

IV (3SLS) regression with robust standard errors, No of obs = 871

Innovations output equation 16:			Productivity growth equation 17:		
Chi2	=	673.6500	Chi2	=	307.6800
Probability	=	0.0000	Probability	=	0.0000
R-squared	=	0.4239	R-squared	=	0.2815
Root MSE	=	1.2037	Root MSE	=	0.2815

Notes: For definitions of the variables see Table 1. Stata is used for the estimation.