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MANAGEMENT CHARACTERISTICS, COLLABORATION AND INNOVATIVE EFFICIENCY: EVIDENCE FROM UK SURVEY DATA

Centre for Business Research, University of Cambridge
Working Paper No. 311

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September 2005

This Working Paper forms part of the CBR Research Programme on Enterprise and Innovation.

Abstract
This paper explores the impact of management characteristics and patterns of collaboration on a firm's innovation performance in transforming innovation resources into commercially successful outputs. These questions are investigated using a recent firm level survey database for 465 innovative British small and medium enterprises (SMEs) over the years 1998-2001. Both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are employed to benchmark a firm's innovative efficiency against best practice. Quality and the variety of innovations are taken into account by combining Principal Component Analysis (PCA) with DEA. We find evidence suggesting that the innovative efficiency of SMEs is significantly affected by their management characteristics and collaboration behaviour. Collaboration, organisational flexibility, formality in management systems and incentive schemes are found to contribute significantly to a firm's innovative efficiency. Managerial share-ownership also shows some positive effect. The importance of these effects, however, varies across different sectors. WE find that innovative efficiency in high-tech SMEs is significantly enhanced by collaboration, formal management structure and training; and that in medium- and low-tech SMEs is significantly associated with managerial ownership, incentive schemes and organisational flexibility.

JEL Classification: D24, O30, O32, L20, M11

Keywords: management characteristics, collaboration, innovative efficiency

Acknowledgements
We are grateful to Bronwyn Hall, Anna Bullock and the reviewers and participants of the Academy of Management 2005 Annual Meeting, 9th European Workshop on Efficiency and Productivity Analysis, and the Cambridge-MIT Competitiveness Forum for helpful comments. We also thank Cambridge-MIT Institute and **i**10 (UK) for generous funding.

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INTRODUCTION

Innovation performance of organisations is determined not only by their resources and innovation inputs, but more importantly, by their productivity in innovation and the factors that affect this productivity. Innovation is not a simple linear transformation with basic science and other inputs at one end of a chain and commercialisation at the other (Hughes, 2003). Successful innovation requires more than brilliant scientists. It takes leaders, entrepreneurial spirit, great ideas, good management, and the right organisational structures (Hjelt, 2005). It requires high-quality decision-making, long-range planning, motivation and management techniques, coordination, and efficient R&D, production and marketing. Therefore, the innovation performance of a firm is determined not only by 'hard' factors such as R&D manpower and R&D investment, but also by certain factors such as management practices and governance structures (Aghion and Tirole, 1994; Bessant et al., 1996; Black and Lynch (2001); Bertrand and Schoar (2003); and Cosh et al., 2004). Top management characteristics, leadership, synergy between departments, research partnerships, marketing efficiency and human resource management are all found to be closely correlated with a firm's propensity to innovate (Hoffman and Hegarty, 1993; Bughin and Jacques, 1994; Nam and Tatum, 1997; Goes and Park, 1997; Tsai, 2001; and Laursen and Foss, 2003). The concentration of share ownership, institutional ownership, external ownership and CEO compensation schemes are also found to be related to the R&D intensity, or innovation propensity, of firms (Kochhar and David, 1996; Love et al., 1996; Bishop and Wiseman, 1999; Chowdhury and Geringer, 2001; Balkin et al., 2002; Czarnitzki and Kraft, 2004; and Hosono et al., 2004).

While substantial work has been done on a firm's propensity for innovation, research on the productivity of innovation is limited. Comparing the difference between Japan and the US in innovation cost and time, with special emphasis on the use of internal versus external technology, Mansfield (1988) finds the Japanese have great advantages in carrying out innovations based on external technology but not internal technology. Firm size and spillovers, in particular from academic sources, are also found to be positively correlated with industrial research productivity (Henderson and Cockburn, 1996; Adams, 2000; and Siegel et al., 2003). Experiences and alliances are found to contribute to research productivity in the pharmaceutical industry (Danzon et al., 2003); public versus private ownership is argued to be a contributing factor in the cross-sectional variance of R&D efficiencies (Zhang et al., 2003). Composing a patent quality index using a linear combination of observed indicators, a recent study by Lanjouw and Schankerman (2004) finds that research productivity at the firm level, measured by the number of patents divided by R&D, is inversely related to patent quality and the level of demand. A brief summary of the literature is presented in Table I.

Table I. A summary of selected literature on industrial research productivity

Study	Country	Sample	Method	Measure of research productivity	Results
Mansfield, E. (1988)	US and Japan	50 Japanese and 75 US major firms in 6 manufacturing industries, 1985	Questionnaire survey, Comparison.	The time and cost of innovation judged by the Chief Executives.	The impact of external and internal technology. The Japanese have great advantages in carrying out innovations based on external technology, but not in carrying out innovations based on internal technology. A large part of US's problem in this regard seems to be due to its apparent inability to match Japan as a quick and effective user of external technology.
Henderson, R. and Cockburn, I. (1996)	US and European	An unbalanced panel. 38 research programs from 10 firms over 30 years in pharmaceutical industry.	Poisson regression.	Number of patents.	Larger research efforts are more productive, not only because they enjoy economies of scale, but also because they realize the economies of scope by sustaining diverse portfolios of research projects that capture internal and external knowledge spillovers.
Mairesse, J. and Hall, B. (1996)	US and France	Two panels of about 1000 manufacturing firms in the US and France over the 1980s, including large and medium-sized firms.	Regression controlled for simultaneity bias with GMM (Generalised Method of Moments).	Output elasticity of R&D.	The contribution of R&D to sales productivity growth appears to have declined during the 1980s. The role of simultaneity bias is higher in the US than in France, possibley reflecting the greater importance of liquidity constraints for R&D investment in that country. Using sales instead of value added does not seriously bias the results.
Adams, J. (2000)	US	220 R&D laboratories in 4 manufacturing industries. 1996.	Postal survey. Negative binomial regressions	Number of patents.	The full effect of spillovers on research productivity of firms exceeds the structural effect. Learning expenditure transmits the effect of spillovers. And it increases in response to industrial and academic R&D spillovers. Academic spillovers appear to have a more pervasive effect on R&D than do industrial spillovers.

Table I. (Continued)

Danzon, P., Nicholson, S. and Pereira, N.S. (2003)	US	900 firms, 1988-2000 in pharmaceutical industry. Large and small firms.	Logistic regressions	Probability of success	Success probabilities are negatively correlated with mean sales by category (which is consistent with a model of dynamic, competitive entry). Success probabilities are larger for products developed in an alliance.
Zhang et al (2003)	China	8341 firms, 1995 large and small firms.	Cross-section regression.	Estimated using Stochastic Frontier Analysis.	Public and private ownership and R&D efficiency. Ownership to be a contributing factor in the cross-sectional variance of R&D efficiencies. The state sector has significantly lower R&D efficiency than the non-state sector.
Siegel, Donald S., Westhead, Paul and Wright, Mike (2003)	UK	Survey data for 89 science park firms and 88 non-science park firms in the late 1980s.	(1). Negative binomial regression. (2) Stochastic frontier analysis and Tobit model	Measures of innovation output: number of new products, number of patents, and number of copyrights, alternatively. (1) Estimates of science park dummy. (2) Estimates of the marginal product of R&D (3) Estimates of SFA	Companies located on university science parks in the United Kingdom have higher research productivity than observationally equivalent firms not located on a university science park. The preliminary results are robust to the use of alternative econometric procedures to assess relative productivity.
Lanjouw, J. O. and Schankerman, M. (2004)	US	Panel data for about 1500 US manafacturing firms over 1980-93.	Develop an index of patent ‘quality’. OLS and IV	Ratio of patents to R&D.	Research productivity at the firm level is inversely related to patent quality and the level of demand.

Prior research therefore shows the importance of internal firm characteristics as determinants of innovation productivity. To date, however, very little is known about the impact of management characteristics and collaboration on innovation productivity. Moreover, most research has explored this issue among large firms. Very few studies have addressed these issues in the context of small and medium enterprises (SMEs), which play a critical role in shaping industrial evolution and are often regarded as a major force in innovation. This study seeks to fill this gap in the literature by examining the impact of management characteristics and collaboration on the efficiency in innovation in the context of SMEs. We use a recent firm level survey data set for a total of 2130 British SMEs for the year 2001.

The study makes several contributions to the literature. First, it attempts to link management science with innovation and industrial economics, and examine the impact of management characteristics and collaboration on the productivity of innovation. As discussed earlier, management and governance systems are crucial factors affecting the innovative productivity of industrial organisations. However, empirical evidence on this issue is surprisingly rare.

Second, this study evaluates innovative efficiency in a multiple-output framework, taking into account different types of innovation and different qualities of innovation, whereas most past research on industrial research productivity uses a single indicator for the measurement of research productivity. We take into account not only sales of new or improved products, but also process and supply system innovations. Quality differences in innovations in terms of novelty have also been controlled for by incorporating Principal Component Analysis (PCA) into the multi-output model. This measures a firm's efficiency in innovation using both parametric and non-parametric frontier analysis benchmarking a firm's observed performance with the best practice. Both stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are employed in the estimation of innovation productivity to cross check the robustness of the results.

Third, firms in different industries have different technology opportunities and innovation strategies. Therefore, management and collaboration variables may impact innovation efforts differently in high-tech SMEs than in other firms. This study explores the different patterns of the effects of management and collaboration across the manufacturing and services, high-technology and medium- and low-technology sectors and discusses its implications. It finds that in the high-technology sector, knowledge-related management factors, such as collaboration, training and formality in management play a crucial role in enhancing innovative efficiency; while in the low- and medium-technology sectors, it is managerial incentives and organisational flexibilities that play an important role in innovative efficiency. The rest of the paper is organised as follows. Section 2 briefly discusses the theoretical framework and the hypotheses. Section 3 addresses the methodology. Section 4 discusses the data. Section 5 presents the econometric results. Section 6 concludes.

THEORY AND HYPOTHESES

Most of the literature investigating the innovativeness of firms assumes that the roles of creator, owner, user and financier of innovation are performed simultaneously by the same person. In practice, however, the creator, owner, user and financier of innovations are, in most cases, not the same party. They may have different interests and motivations which may give rise to agency problems, free-riding and extra transaction costs (Aghion and Tirole, 1994). Therefore, management characteristics and governance structure may both affect a firm's innovation performance.

- **Managerial ownership**

Innovation requires continuous investment in R&D so as to sustain a firm's capability to innovate at the cutting edge of technology (Jelinek & Schoonhoven, 1993). Innovation activities also involve considerable risk since less than 20% of all new product introductions succeed (Crawford, 1987); and even the few projects that do survive are typically unprofitable during their first few years (Block & MacMillan, 1993). Success in innovation, therefore, requires strong managerial support (Nam and Tatum, 1997; Kuratko et al., 1997; Scott and Bruce, 1994). Top managers' commitment to beating the competition, their attitude towards innovation and willingness to take risks all affect firms' strategic decision-making (Papadakis and Barwise, 2002).

However, agency theory suggests that when ownership is separated from management, the objectives of managers and owners may diverge. Lack of an ownership interest in the companies they manage, may cause a lack of the willingness on the part of executives to support innovation (Wright et al., 1996). The executives may behave opportunistically by supporting projects that increase their own wealth. They may pursue short-term objectives instead of the long-run growth of the company. They will lack the incentives to support innovation which may put their positions at risk and which may require new skills (Fama and Jensen, 1983; Wright et al., 1996). This may therefore give rise to X-inefficiency in innovation as top management plays an important role in decision-making, innovation planning and management in small firms.

The alignment effect of managerial share-ownership may reduce the agency problem to certain extent (Jensen and Meckling, 1976). Increased levels of executive ownership make executives' wealth more dependent on their companies' long-term performance. This gives executives an incentive to support innovation which may raise the competitiveness of their companies in the long run (Jenkins & Seiler, 1990; Zahra et al., 2000). Managerial share-ownership can also empower managers to initiate innovation activities (Finkelstein and D'aveni, 1994). The ownership interest for managers may motivate them to make more effort in R&D project decision making, resource allocation and innovation management (Jensen and Meckling, 1976). Therefore,

H1: Managerial share-ownership will be positively related to innovative efficiency.

When a firm is managed by the owner, the so-called agency problem may be greatly reduced as managers' objectives are consistent with those of the owners. However, owner-managed firms behave differently depending on their strategic orientation. Owner-managers of smaller private firms may have primary goals other than financial profitability and wealth objectives (Barton and Matthews, 1989; Poutziouris, 2003). Given the overlap between management and ownership, the strategic orientation of the owner-managed firms may be influenced by non-financial, entrepreneurial and behavioural factors (Michaelas, et al., 1998). These characteristics of the executives explain a significant variance in their influence on innovation (Hoffman and Hegarty, 1993). Moreover, managerial skills of the owner-managers may be limited in comparison with those of professional managers. Given the heterogeneity among the owner-managers and both positive and negative effects of owner-management on innovation, we are unlikely to find a simple link between ownership and innovation.

- **Incentive schemes**

Ultimately, the individual managers and employees in an organization are the ones who generate and implement new ideas, but they may not benefit from their outcomes. The presence of the agency problem may give rise to X-inefficiency (Leibenstein, 1978; Button and Weyman-Jones, 1992), and subsequently reduce a firm's efficiency in innovation. The incorporation of accountability through performance-related payment schemes for managers and employees is found to have a significant correlation with various indicators of business performance (e.g., Fu and Balasubramanyam, 2003; Black and Lynch, 2004). We could expect that this type of incentive scheme, which may motivate not only the managers but also the scientists and all other employees to make their most efforts, will as a result enhance X-efficiency in innovation. Therefore,

H2: Firms that use performance-related pay will be more efficient in innovation than those which did not.

- **Organisational flexibility**

Innovation requires organizational flexibility to facilitate the coordination between the departments within the innovating firm, and to manage change, foster new ideas and effectively commercialize them (Miller and Toulouse, 1986; Wissema et al., 1980). Moreover, a flexible organization structure helps to reduce the transaction costs within organisations. From the evolutionary theory perspective, innovation is an accumulative learning process with an irreversible nature with regard to the technological path (Malerba and Orsenigo, 1990; Pavitt, 1987). A flexible organization structure can facilitate learning from external sources, adaptation of best practices and exploitation of existing information. Therefore, such an organizational structure will provide a favourable environment for the generation and fostering of new ideas. Conversely, a high degree of organizational rigidity increases transaction costs and hampers necessary structural changes for innovation. It reduces not only a firm's propensity of innovation (Bughin and Jacques, 1994; Galende and de la Fuente, 2003), but also the productivity of innovation. Therefore,

H3: A firm with a flexible organizational structure will be more efficient in innovation.

- **Formality in management structure**

SMEs often adopt an informal management structure. The debate over the benefits of organic and mechanistic (formal) management systems is well documented. Burns and Stalker (1961) argue that a mechanistic management system, characterized by specialised differentiation of functional tasks precise definition of rights, obligations and hierarchy, is appropriate to stable conditions, whereas organic structures, characterised by 'realistic' and continually re-defined individual tasks through interaction, spread commitment to the concern beyond any technical definition, and give rise to a lateral rather than a vertical direction of communication through the organization, are appropriate to dynamic environment. On the other hand, Weber (1947) states that bureaucratic organisation, with its clear cut division of activities, assignment of roles and hierarchically arranged authority, is "technically superior to all other forms of organization". Formal structures enable greater precision, speed, task knowledge and continuity. They also reduce friction and ambiguity. The relative lack of structure that characterizes new firms is a liability not a benefit (Stinchcombe, 1965). Firms with informal management structures are less able to adopt cost leadership strategies that require sophisticated cost, budget and profit controls. It is unlikely that such simple structures could adequately support a broad product-market scope or extensive diversification (Miller and Toulouse, 1986). Informality is found to be associated with the relative absence of a wide range of efficiency enhancing management techniques even allowing for size (Cosh and Hughes, 2003).

Formal structure is found to raise new venture turnover in dynamic emerging economic sectors (Sine et al., 2004), and enhance a firm's propensity to innovation. Therefore,

H4: Firms with an informal management structure will be less efficient in innovation than those with a formal management structure.

- **Training**

Innovation is an activity in which human capital rather than physical capital plays a key role. Active human resource management is argued to be an essential contributor to firms' innovation capacity (Laursen and Foss 2003). There is considerable literature on the relationship between training and the propensity for innovation. Cosh et al. (2000) and Baldwin and Yates (1999) argue that there is a two-way relationship between innovation and training. Better labour and managerial skills leads to more innovation; in the meantime, more innovation creates greater demand for training. As Acemoglu (1997) finds, workers are more willing to invest in their skills by accepting lower wages today if they expect their firms to innovate and pay them higher wages in the future. Similarly, firms are willing to innovate when they expect the quality of the future workforce to be higher when workers invest more in their skills.

What is the impact of training on a firm's productivity of innovation? There is little systematic study on this issue. Empirical studies on the effects of training on firm performance in general provide mixed evidence. While Bartel (1994) finds that formal training helps inefficient manufacturing firms catch up with their peers' average productivity, Black and Lynch (1995 and 1996) fail to find a significant effect of training on firm productivity. In principle, however, increased workforce skills through training are likely to improve not only a firm's likelihood to innovate, but also its efficiency in innovation; fFirms that have trained workers at the time of implementation of the new technology can really reap the quasi-rent generated by innovation (Ballot and Taymaz, 1997). Therefore,

H5: Training is positively associated with firms' efficiency in innovation.

- **Collaboration**

External linkages, both public (including higher education institutions) and private, benefit SME innovation (Hoffman et al, 1998). These linkages can be important sources of knowledge that directly strengthen the technological competences of the SMEs and hence their competitive advantage. Collaboration with customers, suppliers, higher education institutions, even competitors, allows firms to expand their range of expertise, develop specialist products, and achieve various other corporate objectives (Kitson et al., 2001). In recent years, important contributions to innovation from business collaborations, in particular supply chains, have received increasing attention (Porter and Stern, 1999). Networking is found to be positively associated with innovation (Goes and Park, 1997), but there are sector and size variations (Rogers, 2004). In addition, the position of the firm in the network is also important. Tsai (2001) argues that firms tht occupy a central network position can produce more innovations. Hall (2000) argues that universities are contributing to basic research awareness and insight among partners. University participation in research programmes is also found to have a positive impact on firm patenting (Darby et. al., 2003). By sharing complementary knowledge and skills, firms can break through the bottleneck that constrains their innovation activities. Collaboration with competitors and customers provides a firm with greater access to domestic or international markets. This may lead to greater commercial success of the new products, and enhances the productivity of innovation through economics of scale. Collaboration with suppliers may lead to lower costs and better quality of the new products. All this may result in higher productivity of the innovation activities. Hence,

H6: Collaboration will be positively associated with firms' innovative efficiency.

- **Industry characteristics**

Firms in different industry and technological groups have different technological opportunities and therefore different strategies and paths for innovation. In small high-tech companies, a considerable proportion of the owners are scientists or technologists who establish their own small companies to capitalize their ideas. Introduction of the best management practice may play a crucial role in assisting these high-tech SMEs to successfully commercialise their knowledge and skills. Establishing a research partnership may be more important in knowledge-intensive industries than in labour- or capital-intensive industries. Hence,

H7: The impact of management characteristics and collaboration on innovative efficiency is likely to be high in small high-technology firms.

METHOD

Estimation of innovative efficiency

The statistical tests of the foregoing hypotheses are taken in two steps. First, we estimate the innovative efficiency of sampled firms. Second, with this estimate of innovative efficiency as the dependant variable, we employ regression analysis to estimate the impact of the major determinants discussed earlier on innovative efficiency. There are two main methods for the estimation of innovative efficiency. One is a non-parametric programming approach, Data Envelopment Analysis (DEA), another is a parametric production function approach, Stochastic Frontier Analysis (SFA). In the DEA approach, a best-practice function is built empirically from observed inputs and outputs. The efficiency measure of a firm's innovation activity is defined by its position relative to the frontier of best performance established mathematically by the ratio of the weighted sum of outputs to the weighted sum of inputs (Charnes, Cooper and Rhodes, 1978).

For a sample of n firms, if X and Y are the observations on innovation inputs and outputs, assuming variable returns to scale, the firm's innovative efficiency score, θ, is the solution to the linear program problem,

$$
\begin{aligned}
& Max_{\theta,\lambda}\ \theta \\
\text{st.}\quad & -\theta y_i + Y\lambda \geq 0 \\
& x_i - X\lambda \geq 0 \\
& \lambda_i \geq 0 \\
& \sum \lambda_i = 1 \qquad i = 1,\ldots,n.
\end{aligned}
\tag{1}
$$

where θ is a scalar and λ is an nx1 vector of constants. The efficiency score ranges from 0 to 1[i]. If $\theta_k = 1$ and all slacks are zero, the kth firm is deemed to be technically efficient (Cooper et al., 2000).

In the SFA approach, assuming a particular production functional form, technical inefficiency is modelled as a one-sided error term. Assuming a knowledge production function as follows:

$$
y = f(x)\exp(v-u) \tag{2}
$$

where y is innovation output, x is a vector of basic innovation inputs. The stochastic production frontier is $f(x)\exp(v)$, where v is a random disturbance that capture the effects of statistical noise and is distributed as $N(0,\sigma_v^2)$; u is a one side error term representing a variety of features that reflect efficiency. u is independent of v and $u \geq 0$, with certain distribution assumptions, e.g., half-normal and exponential distribution. The technical efficiency (TE) relative to the stochastic frontier is thus defined as

$$\text{TE} = \frac{y}{f(x)\exp(v)} = \exp(-u) \tag{3}$$

The strength of the programming approach lies not only in its lack of parameterisation, but also in that no assumptions are made about the form of the production function. In addition, the programming approach allows us to estimate efficiency with multi-output and -input. This technique has a main shortcoming in that there is no provision for statistical noise or measurement error in the model (Greene, 1997; Norman and Stoker, 1991). The econometric production function approach, however, has its main advantage in that measurement error can be minimised and hypotheses can be tested with statistical rigour, although it has the drawback that the production function is assumed to be known and to be homogeneous across firms or sectors. Given the advantages and disadvantages of the programming and the econometric frontier approaches, we use both methods in the estimation of the innovative efficiency to cross check the robustness of the results.

In the DEA analysis, since our major objective is to maximise innovation output, we concentrate on output-oriented efficiency, which reflects a firm's efficiency in producing maximum innovation output with given inputs, under variable returns to scale (VRS). Output of the innovation creation model is measured by the proportion of sales that relates to new or significantly improved products. This indicator has the advantage over other output innovation indicators (e.g., number of innovations and patents) in that it reflects the extent of the commercial success of the innovations. Inputs in the DEA model include the value of R&D expenditure, the total number of R&D staff and the total number of technologists measured as the weighted sum of average full- and part-time R&D staff technologists[ii], respectively. All the output and inputs are standardised by total sales and total number of employees of each firm, respectively.

However, innovation includes not only product innovation, but also process innovation. In addition, there are also differences in degrees of novelty between innovations. Given that DEA analysis allows for multi-outputs in the model, we include process innovation as another output into our DEA model. Following Adler and Golany (2001), we combine the principal component analysis (PCA) with DEA. Firms' performance in process innovation is summarized using the PCA. PCA explains the variance structure of a matrix of data through linear combinations of variables which captures a large proportion of the variance in the data, and in the meantime, reduce the data to a few principal components. If most of the population variance can be attributed to the a few components, then they can replace the full range of variables without much loss of information. However, in the multi-output DEA case, given the fact that new to industry and new to firm innovations are of different degrees of novelty and that the number of innovations does not reflect their final commercial success, a weight system has to be introduced in the estimation depending on the factors generated from the PCA.

For the Stochastic Frontier Approach, following Siegel et al., (2003), we assume a half-normal distribution for the efficiency component μ, which means the firms are either "on the frontier" or below it. The output of the knowledge production function, *y*, is measured by the value of sales that relates to new or significantly improved products, as in the single-output DEA case. Inputs in the SFA model include the value of R&D expenditure, the total number of R&D staff measured as the sum of weighted average of full- and part-time R&D staff[iii], and general human capital measured by the number of technologist, scientists and senior professionals. All the output and inputs are standardised by total sales and total number of employees of each firm, respectively. The empirical SFA model is therefore as follows:

$$\ln NEWSALE = \eta + \phi \ln RD + \xi \ln RDP + \psi \ln HC + \upsilon - \mu \qquad (4)$$

The effects of management and ownership systems on innovative efficiency

In the second stage we employ regression analysis to estimate the impact of the factors discussed earlier on the innovation efficiency of SMEs. The equation to be estimated is of the following form:

$$IE_i = \alpha + \beta_1 COOP_i + \beta_2 OS_i + \beta_3 PP + \beta_4 OG_i + \beta_5 MS_i + \beta_6 TR_i + \beta_7 FS_i + \beta_8 LCONC_i + \beta_9 SEC_i + \mu \quad (5)$$

where i = 1, …, N indexes firm, IE = innovative efficiency, PP = incentive schemes , OS= ownership structure, OG = organizational rigidity, MS = management system, TR = training. Firm size (*FS)*, industry concentration ratio (*CONC*) and a vector of sector dummies *(SEC*) are included as control variables. Definitions of the variables are given in Appendix 1.

In the estimation of firm innovative efficiency, the efficiency scores have an upper bound of 1.0 and a lower bound of 0.0, the ordinary least squares estimates would be inconsistent. Therefore, the regression model for technical efficiency is specified in form of the Tobit model as follows (Tobin, 1958).

$$IE = \begin{cases} \alpha + \beta X_i + \mu & \text{if } \alpha + \beta X_i + \mu < 1 \\ 1 & \text{otherwise} \end{cases} \quad (6)$$

where X_i is a vector of independent variables as listed in equation (5).

Because of possible endogeneity between innovative efficiency on one side, and collaboration and training on the other, we first apply the Wu-Hausman specification test to test for endogeneity. Firms' limitations in financial resources, in access to domestic and international markets, in skilled labour, in management and marketing skills and their difficulty in implementing new technology, in recruiting skilled manual workers, technologists, scientists and managerial staff, the rate of labour turnover and all other exogenous variables in the model are used as predetermined variables. If endogeneity is detected between innovative efficiency and collaboration and training, we utilise the 2-stage Tobit model for estimation, otherwise we use the standard Tobit model.

DATA

Data for this study is collected from the 'Small and Medium Sized Business Survey 2002' (CBR2002) conducted by the Centre for Business Research at Cambridge University for 2130 SMEs in the British manufacturing and business services sectors over the period 1999-2002. The SMEs in the CBR2002 sample is defined as firms that have less than 500 employees. Differently from most of the surveys on SMEs, CBR2002 also covers micro firms in the 1-9 employee band. The survey questionnaire covers not only innovation and business performance, but also management and ownership characteristics. The rich information embedded in this survey allows us to explore the impact of management and ownership on SME innovative capacity and compare the difference between micro, small and medium firms. Of the total 2130 SMEs, 978 firms reported themselves to have either product or process innovation. Because the data envelopment analysis (DEA) requires inputs and outputs to be positive, all the observations with zero new sales, zero R&D expenditure or zero R&D staff are excluded from the sample. After pair-wise deletion of missing observations and outliers with zero values in new sales, R&D expenditure or R&D staff, the number of cases entering the final sample is 465. The mean value of the number of employees in each firm is 66. Twenty percent of them are micro firms in the 1-9 size band; 36 percent are small firms in the 10-49 size band; and 44 percent of them are medium firms in the 50-499 size band. Details of the data and how they were collected are contained in Cosh and Hughes (2003).

In addition, the results of a PCA can be negative. According to Charnes et al. (1985) and Ali and Seiford (1990), an affine transformation of data can be utilised with no change in the results when using the additive model or without a change in the definition of efficient DMUs when using the BCC model. The BCC output-oriented model is input translation invariant (Pastor, 1996). Therefore, following Adler and Golany (2001), all the factors produced from PCA used subsequently in the DEA have been increased by the most negative value in the vector plus one when necessary, thus ensuring strictly positive data for the DEA. The translation is as follows,

$$FAC' = FAC + a,$$

where FAC is the factors derived from PCA, and $a = Min\{FAC\} + 1$.

RESULTS

Table II presents means, standard deviations and correlations among variables. Fifty-three percent of the firms have invested in R&D, 69 percent of them have product or process innovation, and the average share of new products in total sales is 26 percent. On average, 49 percent of the ordinary share is owned by CEs, 11 percent of the firms have introduced stock option schemes and 40 percent have used performance related pay. About 30 percent of the firms have reported an informal management structure, but in 75 percent of the firms the CEs have the personal control of strategic and operating decisions. The magnitude of the correlation coefficients between the independent variables is not large, less than 0.30 in most of the cases. This indicates that multicollinearity does not present a significant problem and that all the independent variables could be included in the regressions[iv].

Table II. Descriptive Statistics and Correlation Coefficients

	Mean	Std.Dev.	Minimum	Maximum	1	2	3	4	5	7	8	9	10	11	12	13
1 NEWSALE	42.644	27.609	1.000	100.000	1.000											
2 RD	0.164	0.203	0.004	1.350	0.227	1.000										
3 HC	0.151	0.250	0.000	1.170	0.226	0.387	1.000									
4 FS	66.050	72.047	1.000	398.000	-0.102	-0.344	-0.181	1.000								
5 COOP	0.527	0.500	0.000	1.000	0.121	0.049	0.139	0.168	1.000							
7 CONC	2.629	0.737	1.099	4.431	-0.042	0.019	-0.088	0.038	0.000	1.000						
8 OS	52.214	32.545	0.000	100.000	0.111	0.107	0.063	-0.278	-0.124	-0.110	1.000					
9 MS	0.271	0.445	0.000	1.000	-0.081	0.252	0.070	-0.347	-0.208	-0.030	0.164	1.000				
10OG	1.567	0.872	1.000	5.000	-0.153	-0.077	-0.126	0.107	0.041	-0.027	-0.055	-0.073	1.000			
11PP	0.449	0.498	0.000	1.000	0.130	-0.034	0.079	0.138	0.102	-0.031	-0.014	-0.102	0.016	1.000		
12TR1	0.761	0.427	0.000	1.000	-0.009	-0.308	-0.124	0.307	-0.003	-0.107	-0.142	-0.310	0.017	0.129	1.000	
13TR2	1.494	1.572	0.010	5.010	0.107	-0.072	0.009	0.137	0.039	-0.127	0.025	-0.127	-0.040	0.185	0.542	1.000

Frontier estimates of innovative efficiency

The innovative efficiency of firms is estimated using both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The process and supply systems innovation outputs were summarized using Principal Component Analysis (PCA). There are two factors which explain 52% of the variance across all the underlying variables. These two factors are retained and extracted, and the estimated 'factor loadings' which represent the weights attached to each underlying variable in the factor are reported in Table III. These two factors are: process and supply system innovation new to firm (FAC1) and process and supply system innovation new to industry (FAC2). The latter factor has higher quality in terms of novelty.

Table III. Factor loadings of innovation outputs

	FAC1 Innovation New to firm	FAC2 Innovation New to industry
Innov new to firm not industry:manuf production methods	.726	2.319E-02
Innov new to firm not industry:supply systems, manuf prod	.777	8.824E-02
Innov new to firm not industry:service production methods	.649	.117
Innov new to firm and industry:manuf production methods	1.974E-02	.747
Innov new to firm and industry:supply systems, manuf prod	.131	.700
Innov new to firm and industry:service production methods	7.683E-02	.681

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 3 iterations.

For the DEA analysis, the efficiency is estimated in three scenarios when innovation output is measured by (1) sales relates to new or improved products, (2) new sales and the two principal components without weights, and (3) new sales and the two principal components with weights restriction. The new sales variable indicates the extent of commercial success of the innovation. We assume it has the same quality as the new to industry process and supply system innovations, and their importance are twice that of the new to firm innovations. Therefore, the weights restriction we use in the 3-outputs DEA model is as follows: [v]

$$q_{\text{newsale}} = q_{\text{new to industry innovation}} = 2\, q_{\text{new to firm innovation}}$$

As Table IV shows, the three DEA estimates and the SFA estimate are, in general, highly correlated with each other. The estimated correlation coefficients between the single-output DEA estimates (DEA1) on one hand, and the weighted 3-output DEA estimates (DEA3w) and SFA estimates (SFA1) on the other hand, are higher than 0.90. The SFA estimates (SFA1) have the lowest variance as this approach has controlled for statistical noise. The impact-weighted, quality-adjusted multi-output DEA estimates (DEA3w) have the lowest standard deviations among the three DEA estimates. The differences in standard deviations between these estimates are, however, very small. These results seem to suggest that the percentage of sales on account of new or improved products has, to certain extent, captured inter-firm variations in innovation, both the type and the quality.

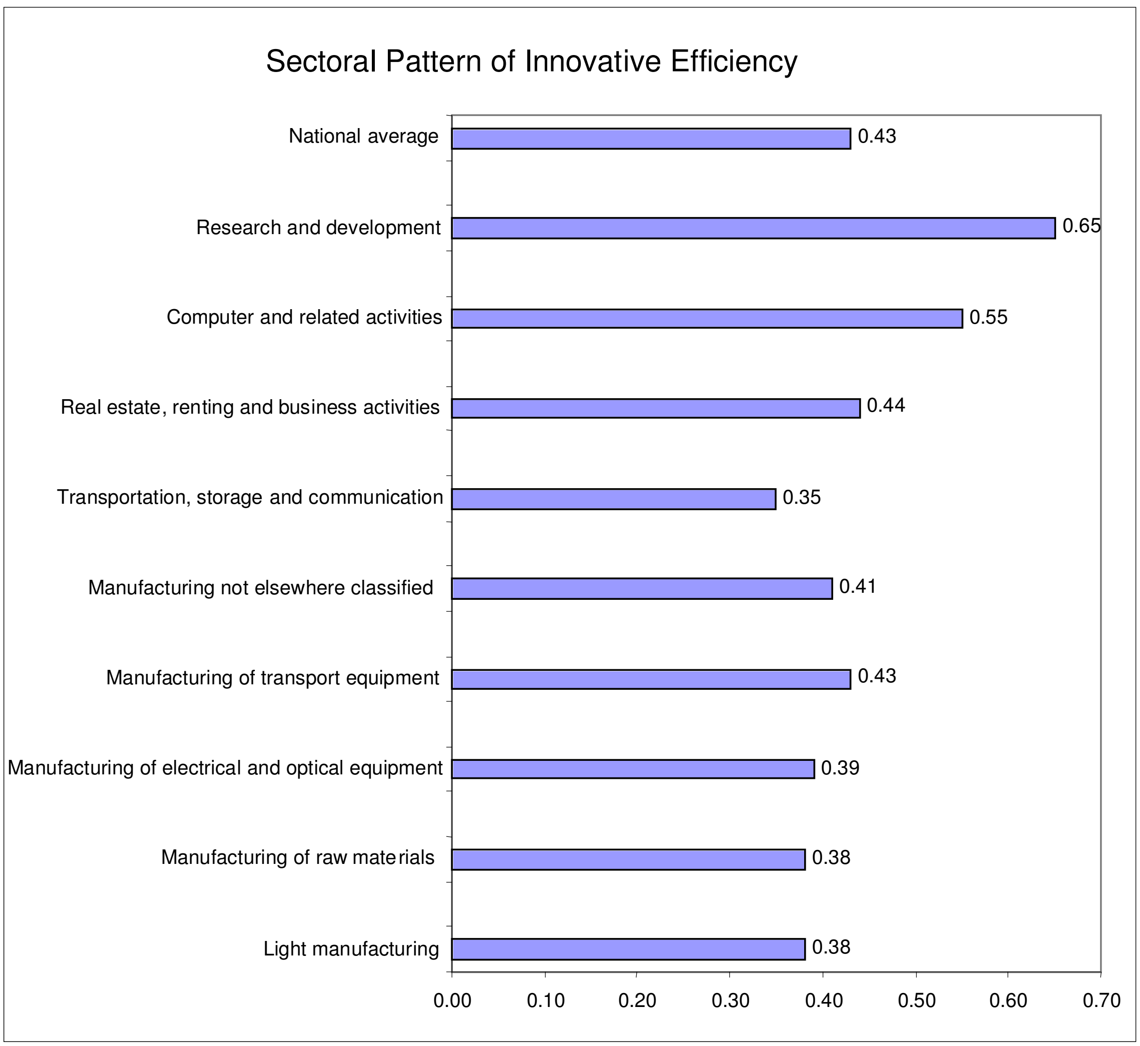
Table IV. Innovative efficiencies of firms

Part 1. Descriptive Statistics				
Variable	DEA1	DEA3	DEA3w	SFA1
Mean	0.432	0.576	0.497	0.511
Std.Dev.	0.279	0.266	0.263	0.255
Minimum	0.01	0.118	0.075	0.015
Maximum	1	1	1	0.896
Skewness	0.617	0.208	0.518	-0.213
Kurtosis	2.248	1.891	2.163	1.723
Cases	465	465	465	465
Part 2. Correlation coefficients				
	DEA1	DEA3	DEA3w	SFA1
DEA1	1			
DEA3	0.739	1		
DEA3w	0.922	0.873	1	
SFA1	0.915	0.675	0.848	1
Part 3. Order statistics				
Percentile	DEA1	DEA3	DEA3w	SFA1
Min.	1.00E-02	0.118	7.48E-02	1.52E-02
10th	0.100	0.250	0.180	0.142
20th	0.200	0.353	0.250	0.237
25th	0.200	0.377	0.295	0.286
30th	0.200	0.380	0.309	0.320
40th	0.300	0.463	0.399	0.443
Med.	0.400	0.550	0.439	0.544
60th	0.500	0.614	0.516	0.623
70th	0.600	0.741	0.600	0.707
75th	0.600	0.765	0.700	0.747
80th	0.700	0.891	0.750	0.779
90th	0.900	1.000	0.919	0.837
Max.	1.000	1.000	1.000	0.896

Notes: DEA1: DEA 1-output model estimates;
DEA3: DEA 3-outputs model (no weights) estimates;
DEA3w: DEA 3-outputs model (with weights) estimates;
SFA1: SFA estimates

Breaking down the efficiency scores across the industries, Figure 1 shows that the Research and Development sector (SIC73) had the highest average innovative efficiency at 0.65 suggesting that, compared to other industry sectors in UK, they are the most efficient sector in transforming innovation inputs into outputs. This result is not unexpected as this sector should have the most experience in innovation management. The computer and related activities (SIC72) sector also enjoy a relative high average innovative efficiency at 0.55. The SMEs in the transportation, storage and communication sector (SIC60-64) are the least efficient in transforming innovation inputs into output. The manufacturing sectors do not show significant difference between each other in this score.

Figure 1.



Analysis of determinants of innovative efficiency

What are the determinants of SME innovative efficiency? Table V presents the Tobit model estimation results. Given the heteroskedasticity of SMEs across the economy, Quasi-maximum likelihood (QML) standard errors that are robust to general misspecification are adopted in estimation. As the Wu-Hausman test for endogeneity suggests that there is no significant endogeneity between innovative efficiency on one hand, and collaboration and training cost on the other, the standard Tobit model result is preferred to the 2-stage Tobit model result.

Table V. Management, collaboration and the efficiency of innovation: Tobit model estimation

	Dependent variables										
	SFA1						DEA1				
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value	Co
Constant	0.607***	0.000	0.621***	0.000	0.621***	0.000	0.619***	0.000	0.662***	0.000	0.66
COOP (collaboration)	0.050*	0.057	0.047*	0.070			0.066**	0.029	0.050*	0.084	
SUPPLIER					0.069**	0.032					0.07
CLIENT					-0.020	0.545					-0.0
UNIVER					-0.020	0.633					-0.0
PRIVATE					0.023	0.604					0.0
FIRM					0.043	0.137					0.0
OS (% share by CE)	0.001**	0.045	0.001*	0.065	0.001*	0.051	0.001	0.107	0.001	0.110	0.0
PP (performance related pay)	0.067***	0.008	0.063**	0.015	0.055**	0.032	0.065**	0.026	0.039	0.173	0.0
OG (organization rigidity)	-0.041***	0.004	-0.034**	0.017	-0.035**	0.014	-0.050***	0.002	-0.036**	0.024	-0.0
MS (informal structure)	-0.090**	0.011	-0.094***	0.009	-0.094***	0.008	-0.099**	0.016	-0.086**	0.031	-0.0
TR1 (training dummy)	0.007	0.822					0.014	0.724			
TR2 (training costs)			0.011	0.204	0.011	0.204			0.013	0.170	0.0
LFS (firm size)	-0.01	0.441	-0.015	0.211	-0.015	0.215	-0.041***	0.005	-0.038***	0.007	-0.03
LCONC (industry concentration)	-0.018	0.389	-0.019	0.346	-0.020	0.327	-0.009	0.704	-0.025	0.282	-0.0
SEC3 (Man. of raw materials)	-0.057	0.110	-0.063*	0.077	-0.056	0.119	-0.090**	0.030	-0.113***	0.005	-0.10
SEC4 (Man. of electrical & optical equip.)	-0.041	0.317	-0.047	0.258	-0.049	0.242	-0.005	0.917	-0.042	0.372	-0.0
SEC12 (Real estate & business activities)	-0.031	0.460	-0.035	0.405	-0.039	0.352	-0.010	0.837	-0.095**	0.039	-0.0
SEC13 (Computer & related activities)	-0.039	0.440	-0.037	0.467	-0.040	0.432	0.025	0.673	0.023	0.689	0.0
SEC14 (Research & development)	0.193	0.180	0.174	0.227	0.157	0.281	0.178	0.282	0.161	0.344	0.1
No of observation	377		377		377		437		437		43
Log likelihood	2.917		6.589		9.412		-80.619		-124.299		-122
DECOMP based fit measure	0.439		0.44		0.441		0.406		0.391		0.3

Note: 1. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level. 2. Base industry: Light manufacturing industry. 3. Wu-Hausman test for exogeneity (H0: exogeneity) has been conducted for collaboration and training variables, and the estimated p-values are 0.279 and 0.906, respectively. None of these variables are reported to be endogenous at the 5% significance level. Therefore, the standard Tobit model is preferred to the simultaneous equations model.

The percentage share owned by CE is positively correlated with innovative efficiency and is statistically significant in most specifications at the 10 percent level. This result suggests that the alignment effect of managerial ownership serves to reduce the agency problem and thereby promote X-efficiency in innovation. Incentive schemes exert a significant positive effect on innovative efficiency in most of the specifications. The innovative efficiency for firms that have performance-related-pay scheme (PRP) is about 0.06 units higher than that for the firms without the PRP scheme. This result indicates the significant effect of the incentive scheme in reducing the agency and free-riding problem in the innovation process. With income related to their performances, individuals and groups will make greater effort and better coordination to maximize their performances. This enhances the overall efficiency of the firm including the innovative efficiency.

Organisational rigidities have a statistically significant negative effect on innovative efficiency. The magnitude, the sign and the statistical significance level of the estimated coefficients are robust across the three specifications. This result implies that organisational rigidities significantly increase operational costs within the firm, weaken a firm's adaptability to change, and reduce its efficiency in transforming resources into commercially successful outputs. Informal management structure also shows a consistent significant negative impact on innovative efficiency. In other words, firms that have a formal management system are more efficient in innovation than those that have not.

Collaboration shows a significant positive effect on innovative efficiency. The SMEs who collaborate with others are more efficient in creating innovation. The complementary resources and skills shared through research partnership enable SMEs to innovate more efficiently and effectively. Unlike their impact on innovation propensity, where clients have the significant effect, it is collaboration with suppliers that presents a significant effect on the improvement of innovative efficiency. This fact suggests that customer- and market orientation of the innovation strategy promotes the birth of new products and processes; close linkages with the supply side enable firms to innovate more efficiently. The estimated coefficient of training dummy shows the expected positive sign, but is not statistically significant. This may be due to a sample bias problem as more than 75 percent of the firms in the valid sample have provided formal training to their employees. Measuring training input by the percentage of formal training costs in total labour costs still yields estimated coefficients that are still not statistically significant. Further studies of the specific skills provided in training and their relevance to innovation are needed before we draw a conclusion.

Firm size shows a negative effect on innovative efficiency. It is statistically significant in the regression with DEA-based efficiency score as the dependent variable. There are two possible explanations for this. First, R&D effectiveness is higher in small firms than in large firms as best practice may be more often met in small firms (Rothwell, 1986) and small firms have a relative managerial advantage in innovation (Bughin and Jacques, 1994). The advantage of small firms in innovation management comes not only from R&D department efficiency, but also from synergy between the firm's departments. Second, comparing the two efficiency estimates, the SFA estimates have excluded the statistical noise in measurement. This fact suggests that, controlling for statistical noise, there is no significant difference in innovative efficiency between large and small firms.

The interaction between management characteristics and sectoral specific effects

Our results suggest there exist significant sectoral effects. To further explore the different patterns between the manufacturing and business services sectors and the high-technology and low-technology sectors, we divide the whole sample into two pairs of sub-samples: the manufacturing and business services sub-samples, and the high-tech and low-tech sub-samples. The research and development, computer and related activities and manufacturing of electrical and optical equipment sectors are classified into the high-technology sub-sample. As Table VI reports, organisational flexibility and incentive scheme show a significant effect on innovative efficiency in most sectors. The firms with high organisational rigidity are further away from the innovation frontier. They are less efficient in innovation given the same innovation inputs. SMEs that have adopted performance-related pay are more efficient in innovation.

Table VI. Management, collaboration and the efficiency of innovation in different industry and technology groups

	Dependent variable: SFA1							
	Manufacturing		Services		High-tech		Low-tech	
	Coef	p-value	Coef	p-value	Coef	p-value	Coef	p-value
Constant	0.519***	0.000	0.608***	0.000	0.589***	0.000	0.602***	0.000
COOP	0.027	0.39	0.097**	0.035	0.087*	0.056	0.03	0.308
OS	0.054*	0.085	-.6D-04	0.935	-0.001	0.398	0.001**	0.021
PP	0.001*	0.054	0.096**	0.027	-0.004	0.928	0.106***	0.000
OG	-0.091**	0.028	-0.047*	0.095	-0.027	0.249	-0.044***	0.009
MS	-0.033**	0.044	-0.079	0.233	-0.312***	0.000	-0.041	0.301
TR	0.007	0.501	0.018	0.153	0.038***	0.008	0.001	0.906
LFS	0.007	0.622	-0.049**	0.014	-0.057**	0.016	-0.006	0.651
LCONC	-0.025	0.233	0.023	0.561	0.046	0.172	-0.045**	0.024
No of observation	260		117		115		262	
Log likelihood	8.723		9.454		4.742		12.631	
DECOMP fitness	0.441		0.452		0.438		0.442	

Note: *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Compared with the high-tech and business services sectors, managerial ownership and incentive schemes play a significant positive role in raising innovative efficiency in the manufacturing and low-technology sectors (Table V). This may be due to the fact that in the knowledge-intensive business services and high-tech SMEs, it is often the owners themselves who own the patent rights and control the technology know-how, and the owners tend to act as the CE themselves. Smaller firms are significantly more efficient in innovation than the larger ones in the high-technology and business services sector, but there is no significant size difference in the manufacturing and low-technology sectors.

Compared to the low-technology sector, the innovative efficiency of the high-tech SMEs is significantly promoted by a formal management structure, collaboration and training. The high-tech SMEs who have entered a research partnership, who have adopted a formal management structure and who have invested more in training are more efficient in innovation. The magnitude of the estimated coefficient of the formality variable is much larger than the estimated coefficients of other variables suggesting the great influence of this factor on high-tech SME innovation. SMEs in the high-technology sector are usually spin-outs from universities, research institutes or large high-tech companies to capitalize their creative ideas and knowledge. The owners are usually highly educated in science and engineering, but may be short in managerial skills (Bollinger et al., 1983; and Utterback et. al., 1988). Our results suggest that hiring professional mangers, adopting formal management structures, for instance, establishing a formal marketing division, will help these firms in achieving greater success in commercialising their innovative ideas.

CONCLUSIONS

This paper has investigated the impact of management and ownership on innovative efficiency of SMEs using a recent survey database for British SMEs. We find that managerial, organisational and collaboration factors are significantly associated with the innovative efficiency of firms. Managerial ownership appears to serve to reduce the agency problem, align managers' objectives with that of the owners, motivate the managers to support innovation, and thereby increase a firm's efficiency in innovation. Performance related pay effectively motivates all the employees in the innovating firms and thereby raises efficiency in innovation. Organisational flexibility and formality in management exert robust positive impacts on efficiency in innovation. Firms that face lower degrees of organisational rigidity are more efficient in innovation. Firms that have well defined management structure which is based on functional specialisation, product markets or geographic regions are more efficient in innovation. Research Partnership is also found to contribute significantly to innovative efficiency, as is collaboration with suppliers. The effect of training on innovative efficiency is not statistically significant and further research is needed.

The impact of management characteristics and collaboration on innovative efficiency, however, varies across different industry and technological groups. Collaboration, organisational flexibility and formality in management are the factors that have a robust significant effect on innovative efficiency across the sectors and groups. Managerial ownership and incentive schemes play a significant role in the promotion of innovative efficiency in the manufacturing and low-technology sector, but not in the business services and high-technology sectors. The innovative efficiency of te high-technology SMEs is significantly increased by formality in management, research partnership and training. Evidence from this study suggest that SMEs in the high-technology sector will be much more efficient in commercialising their innovative ideas and inputs by adopting formal management structures, entering into partnerships and providing training to their employees.

NOTES

[1] For the output-oriented efficiency model, we define the efficiency score as the inverse of the estimated score.
[2] The weight is 1 for full-time staff and 0.5 for part-time staff.
[3] The weight is 1 for full-time staff and 0.5 for part-time staff.
[4] Although correlations among independent variables were generally small, the association between firm size and management structure is -0.38. To ensure multicollinearity is not a problem, we conducted the same analyses ,dropping each of these two variables in successive regression equations. the results did not change, indicting that the correlation between firm size and management structure does not bias the results.
[5] We have also carried out the DEA analysis with different weights. The estimated results do not appear to be significantly different.

REFERENCES

Acemoglu, D. (1997). 'Training and innovation in an imperfect labour market'. *The Review of Economic Studies*, **64**, 3, 445-464.

Acs, Z. S. and Audretsch, D. B. (1990). *Innovation and Small Firms*, Cambridge, MA: MIT Press.

Adams, J. D. and Marcu, M. (2004). 'R&D sourcing, joint ventures and innovation: a multiple indicators approach'. NBER working paper 10474.

Adams, J. (2000. Endogenous R&D spillovers and industrial research productivity, NBER Working Paper No 7484.

Adler, N. and Golany, B. (2001). 'Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe'. *European Journal of Operational Research*, **132**, 260-273.

Aghion, P. and Tirole, J. (1994). 'The management of innovation'. *The Quarterly Journal of Economics*, **109**, 4, 1185-1209.

Ali, A.I. and Seiford, L.M. (1990). 'Translation invariance in data envelopment analysis'. *Operations Research Letters*, **9**, 403-405.

Baldwin, J. and Gellatly, G. (2003). *Innovation Strategies and Performance in Small Firms*, Cheltenham and Northampton: Edward Elgar.

Baldwin, J. and Yates, J. (1999). 'Innovation, training and success'. Statistical Canada, Analytical Studies Branch.

Baldwin, J. R. (1997). 'The importance of research and development for innovation in small and large Canadian manufacturing firms'. Research Paper Series No. 107, Ottawa: Statistics Canada.

Ballot, G. and Tay, E. (1997). 'The dynamics of firms in a micro-to-macro model: The role of training, learning and innovation'. *Journal of Evolutionary Economics*, **7,** 4, p435-58.

Bartel, a. P. (1994). 'Productivity gains from the implementation of employee training programmes'. *Industrial Relations*, **33**, 411-25.

Bertand, M. and Schoar, A. (2003). 'Managing with Style: the effect of managers on firm policies'. Quarterly Journal of Economics, 1169-1208.

Bessant, J., Caffyn, S. and Gilbert, J. (1996). 'Learning to manage innovation'. *Technology Analysis & Strategic Management*, **8**, 1, 59-70.

Bishop, P. and Wiseman, N. (1999). 'External ownership and innovation in the United Kingdom'. *Applied Economics*, **31**, 443-450.

Black, S. E. and Lynch, L. M. (2004). 'What's friving the new economy?: the benefits of workplace innovation'. The Economic Journal, **114**, 97-116.

Black, S.E. and Lynch, L.M. (1995). Beyond the incidence of training: evidence from a national employers survey, NBER Working Paper, 5231.

Black, S.E. and Lynch, L.M. (1996). 'Human capital investments and productivity'. *American Economic Review*, **86**, 263-7.

Black, S.E. and Lynch, L.M. (2001). 'How to Compete: the impact of workplace practices and information technology on productivity'. Review of Economics and Statistics, 83(3), 434-445.

Blundell, R., Griffith, R. and Van Reenen, J. (1999). 'Market share, market value and innovation in a panel of British manufacturing firms'. *The Review of Economic Studies*, **66**, 3, 529-554.

Bollinger, L., Katherine H. and. Utterback, J. M. (1983). 'A Review of Literature and Hypotheses on New Technology-Based Firms'. *Research Policy*, **12**, 1, 1-14.

Bughin, J. and Jacques, J.M. (1994). 'Managerial efficiency and the Schumpeterian link between size, market structure and innovation revisited'. *Research Policy*, **23**, 6, 653-659.

Charnes, A., Cooper, W. W. and Rhodes, E. (1978). 'Measuring the Efficiency of Decision Making Units'. *European Journal of Operational Research*, **2**, 6, 429-444.

Charnes, A., Cooper, W.W., Golany, B., Seiford, L., and Stutz, J. (1985). 'foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of Econometrics*, **30**, 91-107.

Cohen, W. and Levin, R. C. (1989). 'Empirical studies of innovation and market structure'. in R. Schmalensee and R. D. Willig (eds.), *Handbook of Industrial Organization: Vol . 2*, Amsterdam: Elsevier Science Publishers.

Cohen, W. (1996). 'Empirical studies of innovative activity'. in P. Stoneman (ed.), *The Handbook of the Economics of Technological Change*, Oxford: Basil Blackwell, 182-264.

Cooke, P., Roper, S. and Wylie, P. (2003). ''The golden thread of innovation' and Northern Ireland's evolving regional innovation system'. *Regional studies*, **37**, 4, 365-379.

Cooper, W. W., Seiford, L. M. and Tone, K. (2000). *Data Envelopment analysis: a comprehensive Text with Models, Applications, References and DEA-Solver Software*, Boston/Dordrecht/ London: Kluwer Academic Publishers.

Cosh, A. and Hughes, A. (2003). *Enterprise Challenged: Policy and Performance in the British SME sector 1999-2002*, ESRC Centre for Business Research, University of Cambridge, Cambridge.

Cosh, A., Hughes, A. and Weeks, M. (2000). 'The relationship between training and employment growth in small and medium-sized enterprises'. Department for Education and Employment, Research Report No. 245, Sheffield.

Cosh, A., Fu, X. and Hughes, A. (2004). 'Innovatability of small and medium enterprises and its determinants: evidence from UK survey data'. Centre for Business Research, University of Cambridge, memo.

Czarnitzki, D. and Kraft, K. (2004). 'Firm leadership and innovative performance: evidence from seven EU countries'. *Small Business Economics*, **22,** 325-332.

Danzon, P., Nicholson, S. and Pereira, N.S. (2003). 'Productivity in pharmaceutical biotechnology R&D: The role of experience and alliances'. NBER working paper w9615.

Darby, M. R., Zucker, L. G. and Wang A. (2003). 'Universities, joint ventures, and success in the Advanced Technology Program'. NBER working paper no. 9463.

Dean, J. W. Jr. and M. R Sharfman (1993). 'Procedural Rationality in the Strategic Decision-making Process'. *Journal of Management Studies*, **30**, 3, pp. 587–610.

Doyle, P. (2001). 'Management structures and marketing strategies in UK industry'. *European Journal of Marketing*, **13**, 5, 319-331.

Fu, X. and Balasubramanayam, V.N. (2003). 'Township and village enterprises in China'. *Journal of Development Studies*, **39**, 4, 27-46.

Furman, J., Porter, M. and Stern, S. (2002). 'The determinants of national innovative capacity'. *Research Policy*, **31**, 899-933.

Galende, J. and de la Fuente, J.M. (2003). 'Internal factors determining a firm's innovative behaviour'. *Research Policy*, **32**, 5, 715-737.

Geroski, P. A. (1990). 'Innovation, technological opportunity, and market structure'. *Oxford Economic Papers*, **42**, 3, 586-602.

Geroski, P.A., Van Reenen, J. and Walters, C. (2002). 'Innovation, patents and cash flow'. in Kleinknecht, A. and Mohnen, P. (eds) *Innovation and Firm Performance: Econometric Explorations of Survey Data*, Palgrave, New York.

Goes, J.B. and Park, S.H. (1997). 'Interorganizational links and innovation: the case of hospital services'. *Academy of management journal*, **40**, 3, 673-696.

Green, W. (1997). 'Frontier production functions'. in M. H. Pesaran and P. Schimidt (eds.), *Handbook of Applied econometrics, vol. II. Microeconomics*, Oxford: Blackwell Publishers.

Grossman, G. M. and Helpman, E. (1990). 'Trade, innovation and growth'. *American Economic Review Papers and Proceedings*, **80**, 2, 86-91.

Haleblian, J. and S. Finkelstein (1993). 'Top Management Team Size, CEO Dominance, and Firm Performance: The Moderating Roles of Environmental Turbulence and Discretion'. *Academy of Management Journal*, **36**, 4, pp. 844–863.

Hall, B. H. (2000). 'Universities as research partners'. NBER working paper no. w.7643.

Harrison, E. F. (1975). *The managerial decision-making process*, Boston: Houghton Mifflin.

Hjelt, P. (2005). 'What it takes to innovate'. FORTUNE, March 7, 52-53.

Henderson, R. and Cockburn, I. (1996). 'Scale, scope and spillovers: the determinants of research productivity in drug discovery'. *The RAND journal of economics*, **27**, 1, 32-59.

Hoffman, F. R. and Maier, N.R.F. (1961). 'Quality and acceptance of problem solutions by member of homogenous and heterogeneous groups, *Journal of Abnormal and Social Psychology*, **58**, 27-32.

Hoffman, K., Parejo, M., Bessant, J. and Perren, L. (1998). 'Small firms, R&D, technology and innovation in the UK: a literature review'. *Technovation*, **18**, 1, 39-73.

Hoffman, R.C. and Hegarty, W. H. (1993). 'Top management influence on innovations: effects of executive characteristics and social culture'. *Journal of Management*, **19**, 3, 549-574.

Hosono, K., Tomiyama, M. and Miyagawa, T. (2004). 'Corporate governance and research and development: evidence from Japan'. *Economics of Innovation and New Technology*, **13**, 2, 141-146.

Hughes, A. (2003). 'Knowledge Transfer, Entrepreneurship and Economic Growth: Some Reflections and Implications for Policy in the Netherlands'. University of Cambridge Centre for Business Research Working Paper no.273.

Jensen, M.C. and Meckling, W.H. (1976). 'Theory of the firm: managerial behavior, agency costs and ownership structure'. *Journal of Financial Economics*, **3**, 305-60.

Lanjouw, J. O. and Schankerman, M. (2004). 'Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators'. *Economic Journal,* Apr2004, **114** 495, 441-466.

Laursen, K. and Foss, N.J. (2003). 'New human resource management practices, complementarities and the impact on innovation performance'. *Cambridge Journal of Economics*, **27**, 243-263.

Leibenstein, H. (1978). 'On the basic proposition of X-Efficiency theory'. *American Economic Review*, **68**, 2, 328-332.

Love, J.H., Ashcroft, B and Dunlop, S. (1996). 'Corporate structure, ownership and the likelihood of innovation'. *Applied Economics*, **28**, 737-746.

Mairesse, J. and Hall, B. H. (1996). 'Estimating the productivity of research and development: an exploration of GMM methods using data on French and United States manufacturing firms'. NBER working paper No. 5501.

Malerba. F. and Orsenigo, L. (1990). 'Technological regimes and patterns of innovation: a theoretical and empirical investigation of the Italian case'. In: Heerthe, A., Perlman, M. (Eds.), *Evolving Technology and Market Structure: Studies in Schumpeterian Economics*. University of Michigan Press, Ann Arbor, MI.

Mansfield, E. (1988). 'The speed and cost of industrial innovation in Japan and the US: external vs. internal technology'. *Management Science*, **34** 10, 1157-68.

Miller, D. and J. M. Toulouse (1986). 'Chief executive personality and corporate strategy and structure in small firms'. *Management Science*, **32**, 11, 1389–1409.

Mowery, D. C., Oxley, J. E. and Silverman, B. S. (1996). 'Strategic alliances and interfirm knowledge transfer'. Strategic Management Journal, **17**, special issue, 77-91.

Nam, C.H. and Tatum, C.B. (1997). 'Leaders and champions for construction innovation'. *Construction Management & Economics*, **15**, 3, 259-271.

Negassi, S. (2004). 'R&D co-operation and innovation: a microeconometric study on French firms'. Research Policy, **33**, 3, 365-385.

Norman, M. and Stoker, B. (1991). *Data Envelopment Analysis: The Assessment of Performance*, Chichester: John Wiley.

Pastor, J. (1996). 'Translation invariance in data envelopment analysis: A generalization'. *Annals of Operations Research*, **66**, 93-102.

Pavitt, K. (1987). 'The objectives of technology policy'. *Science and Public Policy*, **14**, 4, 182-188.

Porter, M. and Stern, S. (1999). *The New Challenge to America's Prosperity: Findings from the Innovation Index*. Council on Competitiveness, Washington, D.C., USA.

Poutxiouris, P. (2003). 'The strategic orientation of owner-managers of small ventures: evidence from the UK small business economy'. *International Journal of Entrepreneurial Behaviour and Research*, **9**, 5, 185-214.

Rogers, M. (2004). 'Networks, firm size and innovation'. Small Business Economics, **22**, 141-153.

Roper, S. (2000). Benchmarking regional innovation: a comparison of Baden-Wurttemberg, Bavaria, Northern Ireland and the Republic of Ireland, Northern Ireland Economic Research Centre Working Paper No. 56, Belfast.

Rothwell, R. (1986). 'The role of small firms in technological innovation'. In Curra, J. eds. *The Survival of the Small Firm*, Gower, London.

Rothwell, R. and Zegveld, W. (1982). *Innovation and the Small and Medium-sized Firm*, London: Frances Pinter.

Scherer, F. M. (1980). *Industrial Market Structure and Economic Performance*, 2nd edn. Chicago: Rand McNally.

Segerstrom, P. S. (1991). 'Innovation, imitation and economic growth'. *The Journal of Political Economy*, **99**, 4, 807-827.

Siegel, D. S., Westhead, P. and Wright, M. (2003). 'Assessing the impact of university science parks on research productivity: exploratory firm-level evidence from the United Kingdom'. *International Journal of Industrial Organization,* **21**, 9, 1357-70.

Symeonidis, G. (2001). 'Price competition, innovation and profitability: theory and UK evidence'. CEPR Discussion Paper No. 2816. Centre for Economic Policy research, London.

Tobin, J. (1958). 'Estimation of relationship for limited dependent variables'. *Econometrica*, **26**, 1, 24-36.

Tsai, W. (2001). 'Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance'. *Academy of management journal*, **44**, 5, 996-1004.

Utterback, J. M., Meyer, M., Roberts, E. and Reitberger, G. (1988). 'Technology and Industrial Innovation in Sweden: A Study of Technology-Based Firms Formed Between 1965 and 1980,' *Research Policy*, **17**, 15-26.

Wissema, J., van Der Pol, H. and Messer, H. (1980). 'Strategic management archetypes'. *Strategic Management Journal*, **1**, 1, 37-47.

Wright, P., Ferris, S.P., Sarin, A., and Awasthi, V. (1996). 'Impact of corporate insider, blockholder, and institutional equity ownership on firm risk taking'. *Academy of Management Journal*, **39**, 2, 441-463.

Zahra, A., Neubaum, D. and Huse, M. (2000). 'Entrepreneurship in medium-size companies: exploring the effects of ownership and governance systems'. *Journal of Management*, **26**, 5, 947-976.

Zhang, A., Zhang, Y. and Zhao, R. (2003). 'A study of the R&D efficiency and productivity of Chinese firms'. *Journal of Comparative Economics*, **31**, 444-464.

APPENDIX

Appendix 1. Definition of variables

Variables	Definition
NEWSALE	Percentage of sales accounted for by new or improved products.
RD	R&D dummy, 1=R&D, 0=no
RDE	R&D expenditure
RDP	Number of R&D staff
HC	number of scientist and technologist
IE	Innovative efficiency estimated in two different ways: DEA and SFA
DEA1	DEA 1-output model innovative efficiency estimates
DEA2	DEA 3-output model innovative efficiency estimates (no weights)
DEA3	DEA 3-output model innovative efficiency estimates (with weights)
SFA1	SFA 1-output model innovative efficiency estimates
OS	Percentage of ordinary shares owned by the chief executive.
PP	Performance related payment dummy, 1=yes, 0=no
OG	Organisational rigidities ranging from 1 to 5 which indicate this is an insignificant barrier and a crucial barrier, respectively.
MS	Management structure dummy, 1 for firms with informal structures and 0 for others
TR1	Training dummy, 1=provide formal training to employees, 0=no
TR2	Training input, measured by the proportion of formal training costs in total labour costs.
COOP	Innovation co-operation agreements dummy, 1=yes, 0=no
SUPPLY	Dummy for co-operation with supplier, 1=yes, 0=no
CLIENT	Dummy for co-operation with client, 1=yes, 0=no
PRIVATE	Dummy for co-operation with private research institutions, 1=yes, 0=no
UNIVER	Dummy for co-operation with university, 1=yes, 0=no
FIRM	Dummy for co-operation with competitor, 1=yes, 0=no
LHC	Log (number of scientist and technologist / total number of employees)
LFS	Log of firm size measured by the number of employee 2000
CONC	Industry concentration ratio measured by the share of turnover of top three enterprise groups in total industry output.
REG	Dummies for each region
SEC	Dummies for each industry group