Author(s): Battisti, Giuliana and Stoneman, Paul

Article Title: How Innovative are UK Firms? Evidence from the Fourth UK Community Innovation Survey on Synergies between Technological and Organizational Innovations

Year of publication: 2010
http://dx.doi.org/ 10.1111/j.1467-8551.2009.00629.x

HOW INNOVATIVE ARE UK FIRMS? EVIDENCE FROM THE CIS4 ON SYNERGIES BETWEEN TECHNOLOGICAL AND ORGANISATIONAL INNOVATIONS

Giuliana Battisti and Paul Stoneman[a]
Nottingham University Business School, Nottingham NG8 1BB, UK,
[a]Warwick Business School, Coventry CV4 7AL, UK
Corresponding author e mail: paul.stoneman@warwick.ac.uk

Acknowledgements. With grateful thanks to our joint doctoral student Amid Mourany for his assistance with some of the statistical material, and to the Department of Trade and Industry (now the Department for Business, Enterprise and Regulatory Reform, BERR) for access to the data and for funding within its study theme of Innovation in Organisational Structures and Management. We also thank two referees and the editors of this journal for comments on an earlier draft. All errors that remain are however the responsibilities of the authors alone.

Key words: organisational innovation, technological innovations, synergies, innovation, adoption, and profitability.

HOW INNOVATIVE ARE UK FIRMS? EVIDENCE FROM THE CIS4 ON SYNERGIES BETWEEN TECHNOLOGICAL AND ORGANISATIONAL INNOVATIONS

Abstract

Using data from the 4th UK Community Innovation Survey (CIS4) this paper explores the diffusion of a range of innovative activities (encompassing process, product, machinery, marketing, organization, management and strategic innovations) across 16383 British companies in 2004. Building upon a simple theoretical model it is shown that the use of each innovation is correlated with the use of all other innovations. It is shown that the range of innovations can be summarised by two multi innovation factors, labelled here 'organisational' and 'technological', that are complements but not substitutes for each other. Three clusters of firms are identified where intensity of use of the two sets of innovation is: below average (56.9% of the sample); intermediate but above average (23.7%); and highly above average (19.4%). Distinctive characteristics are found to be common to the companies in each cluster. Finally, it is shown that innovativeness tends to persist over time.

1. INTRODUCTION

Although much past research has focussed on the productivity gap that exists at the macro level **between** the UK and its major international competitors, including Germany, France and especially the US (O'Mahony and De Boer 2002), it is clear that a productivity gap of some substantial size also exists at the sectoral level **within** the UK and even between firms in given sectors. It is to this latter, micro literature, that this paper contributes and to which an increasing interest is now being paid.

Within the research on productivity there has always been an emphasis upon the role played by technological innovations. More recently research has increasingly emphasised that differences at the firm level may also be a function of how companies are managed. This is in line with Porter and Ketels (2003) who, in their review of the state of the UK competitiveness, suggest that one explanation for productivity gaps is the use and the effectiveness of modern management practices in UK firms. Authors such as Berman et al (1994, 1997), Wengel et. al. (2000), Cappelli and Neumark (2001), Edwards et al (2004) and Bloom and Van Reenen (2007) have also explored the role of new work and management practices in the performance of the firm. They have then argued that that the simple adoption of technological innovations alone is not sufficient to gain competitiveness; the full benefit of those technologies is only achieved if they are accompanied by a cluster of related innovations in production, organization, customer and supplier relationships and new product design. This is equivalent to stating that there are positive synergistic gains to be realised from simultaneous innovation on several fronts. Consequently, any study of the impact of the adoption and use of an innovative practice should not be carried out in isolation from the adoption of other such practices, as this would neglect the potential for synergies and extra gains derived from joint adoption of complementary innovations (see Whittington et al. 1999 or Ruigrok et al. 1999).

An extensive literature has explored the diffusion of technological and managerial innovations in isolation. Most of this literature has also concentrated on one innovation at a time. Robust empirical evidence on the existence of complimentarity across innovations is still quite scarce. As a result, our knowledge of the combined use of, and synergies among, the range of strategic, organisational or managerial innovations is quite limited, let alone the relation of such innovations to the more traditionally considered technological innovative activity.

At least partly, the lack of prior research in this field is due to poor data availability. Innovation that has not involved changes in processes and products have traditionally merited little effort in data collection. In addition, the occasional ad hoc surveys that have been undertaken rarely incorporated information on a full spectrum of management as well as technological innovations. In this paper, we overcome such limitations by using the individual firm level returns data[1] from the Fourth UK Community Innovation Survey[2] which provides information on the use of a wide range of innovative activities carried out by 16383 British companies between 2002 and 2004. This dataset is quite unique in that it contains information on strategic, management, organisational, and marketing innovations as well as on innovations of a more traditional technological nature (such as new machinery, new processes and new products). We use this information to explore the simultaneous use of a wide set of innovations in an attempt to: (i) map out the patterns of use across firms; (ii) explore the determinants of these patterns; (iii) isolate the synergies; and (iv) explore the impacts of joint adoption on firm performance.

The theoretical framework employed here is a simple, decision theoretic, innovation adoption model, based upon profitability considerations, which we extend to allow for synergistic gains derived from the joint adoption of complementary (or potentially substitute) innovations. The model conceptually belongs to a class of equilibrium models used in the literature on the economics of technological diffusion (see Stoneman, 2002 for a review). The resulting model is essentially distribution free, in line with the work of Perrow, (1976) and Birdi et al (2003), does not superimpose certain combinations of innovations as desirable so that 'one fits all', and does not assume that the optimal level of adoption is universally 100%. Rather, driven by profitability considerations, it allows that what is optimal for the firm is firm specific and as conditions internal and external to the firm change, so does profitability and the desired level and combination of the use of the innovations.

When we apply this interpretative framework to our data, we find that significant complementarities arise from the joint use of the different innovations. These complementarities are reflected in the identification of two main sets of innovative factors that we name: ‘organisational’ innovation and ‘technological’ innovation. The former encompasses innovation involving new management practices, new organization, new marketing concepts and new corporate strategies. The latter encompasses technological innovation such as the traditionally measured process and product innovations.

Further to the mapping out of the patterns of use across firms and to isolate the synergistic effect, we are able to identify three clusters of adopting firms which we classify as: intensive, medium and low users. We explore the characteristics of firms in each cluster and the impact of their adoption decision upon their performance. We believe that in this way this study makes a valuable contribution to the understanding of the complexity of the innovation path of UK firms and their performance.

The paper is structured as follows: Section 2 introduces the dataset, the key variables of interest and some initial indicators of new technology usage. Section 3 provides the theoretical model. Section 4 explores revealed synergistic gains in the data. Section 5 uses principle components analysis to identify key factors. Section 6 explores the clustering of the use of these factors across the sample and the impact of firm characteristics on usage. Section 7 explores the impact of innovative activities upon firm performance, section 8 looks at persistence in innovation and section 9 concludes.

2. THE CIS4 DATASET AND MEASURES OF INNOVATIVE ACTIVITY

The Community Innovation Survey (CIS) is a pan-European survey carried out every four years[3] by each EU member state and is designed to gather information on the extent of innovation in European firms across a range of industries and business enterprises. CIS4 is the fourth round of data collection, was carried out in 2005 and relates to innovative activities carried out in the three year period from 2002 to 2004. In the UK this survey was administered by the Office of National Statistics on behalf of the Department of Trade and Industry (DTI). The survey was addressed to enterprises (which we here call firms, although this is misleading for multiplant firms) with more than 10 employees, in both manufacturing and service industries, with response being voluntary. We have been given privileged access by the DTI to the individual returns although we are unable to identify respondents.

From an original sample of 170,735 companies the questionnaire was sent to a stratified (by industry, firm size and geographical region) sample of 28,000 enterprises and 16,383 responses (about 50% response rate) were eventually registered which represent the sample for the work reported here[4]. The salient point for our purpose is that the dataset contains information on a wide range of innovative activities carried out by firms. In particular it contains information on whether, between 2002-2004, the sample companies had introduced: new product innovations (PRODINOV); new process innovations (PROCINOV); and any technological innovation such as new machinery, equipment and computer hardware or software to produce new or significantly improved goods, services, production processes or delivery methods (MACHINE). Further to these traditional indicators of innovative activities, responses to CIS4 question 23 contains information on whether the enterprises have made major changes in the areas of business structure and practices during the three year period 2002-2004 concerning: the implementation of new or significantly changed corporate strategy (STRATEGY); implementation of advanced management techniques (MANAGEMENT); implementation of major changes to the organization structure (ORGANIZATION); and implementation of changed marketing concepts or strategies (MARKETING).

Out of the 16383 enterprises who responded to the CIS4 questionnaire, about 20% have adopted at least one of the innovations, the exception being MACHINE, which has been adopted by about half of the sample. Table 1 reports the variable definitions and the percentage of adopting firms in the sample.

[Table 1 about here]

In Table 2, using the CIS4 data summarised in Table 1, we explore the extent to which firms introduced multiple innovations. We report the Kendall's tau-b correlation coefficient (a non-parametric measure of association based on the number of concordances and discordances in paired observations) for the 7 innovation variables listed above in order to indicate the extent to which the sample firms between 2002 and 2004 undertook simultaneous innovation practices. For all the variables the pair wise degree of association is significantly different from zero showing that adopting one innovative practice or technology is not independent of adopting another innovative practice or technology and that the adoption of all practices is correlated with the adoption of all others. However, the degree of association differs in intensity and varies from innovation to innovation.

[Table 2 about here]

3. THEORETICAL GROUNDINGS

The existence of significantly positive pair wise correlations between the adoption of different innovative practices is not necessarily proof of complementarities and or synergies. The correlations may in fact be the result of other background factors. In this section we therefore approach the issue theoretically in order to provide some grounding for our analysis. The theory in this section is largely built upon approaches standard in the economic analysis of technological diffusion (see Stoneman, 2002, for a review) that for the purpose of this study we extend to the diffusion of the non-technological innovations (see in addition, Battisti and Iona 2007).

Assume an industry (or sector) with N heterogeneous profit maximising firms, i = 1..N, each of which initially can adopt a new practice or technology y in time t with the expected present value of the gross profit gain from adoption of innovation y being $\pi_{it}(y)$. Assume that $\pi_{it}(y)$ is distributed across the N firms according to $F(\pi_{it}(y))$, the distribution being invariant with respect to time and the extent of use of the innovation (an assumption made for the sake of simplicity but which could at the cost of greater complexity be relaxed).

The cost to firm i of acquiring the innovation in time t, $c_{it}(y)$, is assumed to have a component common to all firms, $c_t(y)$, reflecting, say, the charge for buying equipment, plus a firm specific component, e_{it}, reflecting perhaps installation costs such that $c_{it}(y) = c_t(y) + e_{it}(y)$

Assume also that firms are myopic in their expectations formation processes and expect $\pi_{it}(y)$ and $c_{it}(y)$ to remain constant over time. Under such assumptions the profitability and arbitrage conditions for the adoption of an innovation coincide. This assumption removes expectations effects from the model but these could be included and have been in the literature (Ireland and Stoneman, 1986). Firm i will then be expected to adopt innovation y at the first date at which $\pi_{it}(y) - c_{it}(y) \geq 0$. More formally, define a dummy variable $D_{it}(y)$ as equal to 1 if firm i has adopted (only) innovation y in time t and zero otherwise, then $D_{it}(y) = 1$ if $\pi_{it}(y) \geq c_{it}(y)$.

The net gain from adoption, $\pi_{it}(y) - c_{it}(y)$, may increase over time due to either $\pi_{it}(y)$ increasing or $c_{it}(y)$ decreasing. The latter for example may happen if there are reductions in acquisition/adoption costs, the former may happen if, for example, there are quality improvements in innovations over time or externalities derived from use by other companies. However, at a point in time, as $c_t(y)$ is the same for all firms, the cross section usage pattern[5] will only reflect differences across firms in $\pi_{it}(y)$ and $e_{it}(y)$. Thus for example, at time t, firms for whom $\pi_{it}(y)$ is large will be more likely to introduce the innovation than firms for whom $\pi_{it}(y)$ is small. This is particularly relevant as we only have cross section and not time series data.

Recent theoretical and empirical research has increasingly recognized that to look at the adoption of stand alone innovations may be misleading since firms often tend to adopt clusters of innovations rather than individual practices and innovations in isolation. The supposition is that joint adoption of complementary innovations can significantly improve productivity, increase quality and often result in better corporate financial performance relative to isolated instances of innovation. Milgrom and Roberts (1990, 1995), indeed, explicitly claim that bundling more innovative practices together is not an accident. Rather, it is the result of the adoption by profit-maximizing firms of a coherent strategy that exploits complementarities. Similarly, Battisti et al. (2005), within a causality framework, find the existence of extra profit gains from the joint rather than individual adoption of different work practices. Complementary innovations are essentially innovations where the overall net gain from joint adoption is higher than the sum of the net gains from individual adoption (see for example Ichniowski et al. 1997, Whittington et al. 1999, Battisti and Iona 2007 for examples of super-additivity and clusters of innovations, or the formalised models of Battisti et al 2005 or Stoneman 2004 for substitute and complementary technologies, etc.).

To consider such complementarities, assume that there is a second innovation k that is available at the same time as technology y[6]. This innovation k may be adopted in time t by firm i at a cost $c_{it}(k)$, made up, as for y, by a general and a firm specific effect such that $c_{it}(k) = c_t(k) + e_{it}(k)$. If innovation k alone is adopted by firm i in time t then the gross payoff is $\pi_{it}(k)$. If both innovations y and k are introduced the payoff π_{it}(y and k) is assumed to be $\pi_{it}(y) + \pi_{it}(k) + \mu_{yk}$, where μ_{yk} reflects synergies between the two innovations.

The firm has four possible strategies:

1.Adopt neither innovation in which case the net profit gain is zero
2.Adopt only innovation y with a gross present value payoff of $\pi_{it}(y)$
3.Adopt only innovation k with a gross present value payoff of $\pi_{it}(k)$
4.Adopt both innovation y and k with a gross present value payoff π_{it}(y and k)

Of particular interest here is what will encourage firms to adopt several innovations jointly rather than just single innovations i.e. to pursue strategy 4 as opposed to strategies 2 or 3 (or even 0). A profit maximising firm will adopt both innovations if joint adoption is profitable and if the net benefit from adopting an extra innovation having already adopted the other is positive. Thus joint adoption will result if (i) it is profitable to own both innovations i.e. $\pi_{it}(y) + \pi_{it}(k) - c_{it}(y) - c_{it}(k) + \mu_{yk} \geq 0$ (ii) having got innovations y it is profitable to also install k i.e. $\pi_{it}(k) - c_{it}(k) + \mu_{yk} \geq 0$ (iii) and having got k it is profitable to also install y i.e. $\pi_{it}(y) - c_{it}(y) + \mu_{yk} \geq 0$. Ceteris paribus, the greater is μ_{yk} the greater is the chance of these conditions being met and thus the probability of joint adoption increases with μ_{yk}.

One may interpret μ_{yk} as reflecting the synergies between the two innovations and in particular if the innovations are complements then $\mu_{yk} \geq 0$ and if they are substitutes then $\mu_{yk} \leq 0$. If they are not connected then $\mu_{yk} = 0$. The more it is the case that the payoff to one innovation is greater when the other innovations is in use the more one would expect both innovations to be used together (although the conditions show that the innovations do not have to be complements to be jointly in use, as long as they are not too strict substitutes).

Defining the dummy variable $D_{it}(k)$ in line with $D_{it}(y)$ as reflecting use of innovation k, and for simplicity assuming that μ_{yk} is not firm specific, we may now extend the above single innovation conditions for the use of an innovation to state that firm i will be using innovation y in time t if $\pi_{it}(y) + D_{it}(k)\ \mu_{yk} \geq c_{it}(y)$ and be using innovations k in time t if $\pi_{it}(k) + D_{it}(y)\ \mu_{yk} \geq c_{it}(k)$. If μ_{jk} is positive then these conditions imply that complementary effects will increase the likelihood of adoption of the second innovation.

Individual innovative activities can be defined to be complementary (exhibiting synergies) if the adoption of one raises the marginal payoff of others (see also Whittington et al. 1999, Ruigrok et al. 1999, Battisti et al 2005 and Battisti and Iona 2007). In this context, Arora and Gambardella (1990) and Arora (1996), following the revealed preference approach, show that this is equivalent to saying that the second order cross derivative of the expected gain between innovation y and innovation k (μ_{yk} as modelled above) is positive. Such marginal payoff effects will be shown when, in the econometric modelling of the probability of adopting by firms of any one innovation, the conditional covariance between the adoption of any two innovations y and k is positive, after controlling for the impact of a number of firm and environmental characteristics which might act as potential lurking factors[7]. In the next section we undertake such an exercise to isolate patterns of complementarities and synergies across the seven identified innovations in the data base.

The theory above suggests that the cross section pattern of usage at a moment in time, will reflect the stand alone payoffs to individual firms from adoption, which in turn will depend upon: the firm specific cost, e_{it}, for the innovation; the stand alone firm specific gross profits to be earned from the innovation π_{it}; and any synergies available from joint adoption (μ_{ky}). The greater the synergies the more one might expect adoption of multiple rather than single innovations.

4. COMPLEMENTARITIES IN INNOVATIVE ACTIVITIES

Having shown in section 2 above that the CIS4 data reveal significant pair wise correlations in the use of new technologies and practices, we now explore whether, on the basis of the theory detailed in section 3 and the CIS data, we are able to make any empirical inferences on synergies (by seeing, as suggested, whether the conditional covariance between the adoption of any two innovations is positive in the econometric modelling of the probability of adopting by firms of any one innovation).

The key to operationalising the model to explore usage of innovative activities is in specifying the determinants of the differing returns to the use of innovative activities $\pi_{it}(.)$ and also the different firm specific cost effects $e_{it}(.)$, i.e. the different net gains. The rationale behind our approach is that firms are different and as a result get different returns from the use of innovations. These returns reflect different gross profit gains and different firm specific costs. As one cannot necessarily separate cost and revenue effects we will talk below of just different returns without being specific as to whether these result from the cost or revenue side. We define the determinants of the different returns as a vector of firm specific and environmental factors θ_i. It is assumed that the characteristics that determine the differences in returns are not themselves affected by the firm's own innovation adoption.

There is an extensive theoretical and empirical literature that looks at what the relevant characteristics might be (see Geroski, 2000). The firm and environmental characteristics that we have included have been partly dictated by the economic analysis of technology diffusion and partly by data availability. They are listed below and summarised in Table 3 (as we are here primarily interested in analysing cross sectional data and thus differences across firms at a point in time, from this point on, we drop the t subscript and, where not necessary, also the i subscript).

(i) Firm size (SIZE) measured by the number of employees. Size may pick up a number of other firm characteristics such as efficiency, management abilities (see Astebro, 1995) and perhaps past innovations and may also reflect any scale economies that there might be in the use of innovations. It may also pick up whether the unit cost of innovation varies with firm size. Firm size has a long history as a deterministic factor in diffusion studies (see for example Mansfield (1968), Hannan and MacDowell (1984), Karshenas and Stoneman (1993), Saloner and Shephard (1995), Colombo and Mosconi (1995), and Astebro (2002)) it generally being found that size of the establishment exerts a significant and positive impact upon innovation adoption.

(ii) R&D Intensity, R&D, which takes the value one if the firm reports R&D activity in the period 2002 - 2004 and zero otherwise. This variable reflects the Schumpeterian hypothesis that formalised R&D exerts a positive impact upon the use of innovations, in line with Cohen and Levinthal (1989).

(iv) The covariates SCdegree and OTHdegree measuring the percentage of employees with a degree in Science or Other degrees in 2004. The importance of skills has been emphasised by, for example, the pioneer work of Finegold and Soskice (1988) who first defined the concept of low skills/ low quality equilibrium or more specifically by the work on links between innovation and skills by Bartel and Lichtenberg, 1987, Caroli and Van Reenen, 2001 and Bresnahan et. al. 2002 etc.[8]

(vi) Whether the firm was established after 2000 (AGE). The age of the establishment is included according to the view that older plants generally have more experience that allows them to assess costs and benefits of any changes better than younger plants (see for example Noteboom 1993). Nevertheless, older plants might also be less flexible in introducing innovations due to the nature and complexity of their organizational structure (see Little and Triest 1996, Battisti et al 2005) or the resistance of employees to the introduction of innovations (see Ichniowski and Shaw. 1995). In the CIS4 questionnaire there is a question on whether the company was established after 1^{ST} of January 2000. We use it as a proxy for young and old establishments

(vii) Three other dummy variables that have been linked to early adoption of innovations in previous literatures (see Stoneman and Battisti, 2008) capture whether the firm belongs to a group (GROUP), whether the market for its final product is international (INTERNAT), and whether the company received any public financial support (SUPPORTPU).

(viii) We also include a series of 12 industry dummy variables to reflect different industry (wider subgroup) conditions, markets, and types of innovations and payoffs to firms in different industries. The industrial classification follows the SIC 92 as defined in Appendix 1.

[Table 3 about here]

To econometrically model the probability of adoption by firms of single innovations we undertook 7 probit model estimations, one for each innovation, that relate adoption/non adoption of the innovation by the firm to the firm characteristics in the vector θ_i. The estimates yield the results presented in Table 4.

[**Table 4 about here]**

The coefficient estimates are largely in line with our prior expectations as far as sign and significance are concerned (but these are not our main interest). The main interest is in the results on the significance and signs of the off diagonal elements of the covariance matrix of the standardized residuals of the probit specifications (R_j) where j= process, product, machinery, marketing, organization, management and strategic innovations), and these are reported in Table 5. The degree of association, i.e. the extent of the complementarity effect "μ_{yk}", is significant and positive for all pair-wise comparisons although it varies and differs in intensity from pair to pair of innovations (for example management and strategy illustrate greater synergy than product and strategy). This suggests that there exist important synergies generated by joint adoption although some innovations are more influential and versatile than others. The implication is that to concentrate on the analysis of the adoption of single innovations in isolation would be misleading, and it is far preferable to consider the joint adoption of complementary innovations.

[Table 5 about here]

5. THE INTENSITY AND CLUSTERING OF INNOVATIVE ACTIVITY

Thus far we have proceeded by analysing the seven different technologies as separate, but involving synergies. This is a cumbersome procedure and there are considerable analytical advantages if the number of innovation variables to be analysed can be reduced. Principle components analysis is a commonly used tool for dimensionality reduction in data sets while retaining those characteristics of the data set that contribute most to its variance by keeping lower-order principal components and ignoring higher-order ones. Here we perform iterated principal factor analysis (IPFA) based upon the decomposition of the tetrachoric correlation matrix of the pair wise adoption decision for the firms in the CIS4 sample. This identifies the underlying pattern of intensity of use of different innovative practices by the sample of UK firms in 2004. We do not make any presumptions as to what is the “best” combination of innovations (see, for example, Perrow 1967). We instead let the data inform on the variability and the intensity of use of the different practices based upon the extent of their natural association.

IPFA models the correlations amongst the innovations adopted and linearly transforms them to obtain a smaller set of variables uncorrelated with (orthogonal to) each other and defined so that the first factors are the vectors of coefficients (loadings) of the linear combination that explain the largest proportion of variance. In other terms, IPFA allows one to summarize the heterogeneity of use of the set of the 7 innovations via a reduced number of latent factors capable of picking up the underlying pattern of use that can explain the largest proportion of variability of the joint adoptions and so identify the innovative practices that play the major roles in the overall innovative activities of the firm

In Table 6 we report the tetrachoric correlation matrix for the use of different innovations. The highest correlations have been found between process and product innovation and among new strategy, management, organization and marketing practices. The Kaiser-Meyer-Olkin measure of overall sampling indicates whether the sum of partial correlations is large relative to the sum of correlations and the value of 0.8652 being close to 1 indicates that patterns of partial correlations are relatively compact and so factor analysis should yield distinct and reliable factors. The Bartlett measure of sphericity is significantly different from zero at the 1% significance level indicating that the original correlation matrix is not an identity matrix and thus that the factor analysis is appropriate for this data.

In Table 7 we report the rotated[9] factors loadings and their uniqueness. While the former are the coefficients of the linear combination of the original variables that decreasingly explain the largest part of the variability, the latter measure the proportion of variance of the variable that is not accounted for by all of the factors taken together[10]. The first factor (Factor 1) accounts for 83.5% (57% if rotated) of the total variability in firms' innovative activity and it is driven by the extent of use of strategy, management, organizational and marketing innovations. These are labelled in CIS 4 as wider innovations (defined as 'new or significantly amended forms of organization, business structures or practices, aimed at step changes in internal efficiency of effectiveness or in approaching markets and customers') but we prefer the label organisational innovations.

[Table 6 about here]

The second factor (Factor 2) in Table 7 explains 16.5% (43% if rotated) of the remaining variability in the heterogeneity of use of innovative activities by the firms in the sample and it is driven by product, process and technological innovations, which we generally label technological innovations. The overall pattern can be better seen in Figure 1 that reports the rotated factor loadings on the two axes. On the x axis the principal factor shows the importance of organisational innovations, while on the y-axis the second factor shows the importance of technological innovations.

[Table 7 about here]

[Figure 1 about here]

For all the variables used in the IPFA analysis the uniqueness statistic indicates that most of their heterogeneity of use is largely related to the other extent of use variables. Interestingly, MACHINERY is the innovation that has the least shared variance and is the most adopted (in fact about 47% of the firms in the sample employ this innovation). As MACHINERY incorporates software and PCs it may be that Information Technology has become so widespread that it no longer yields a competitive advantage to adopters. The latter is consistent with the observation that MACHINERY is the dominating factor load in the third factor extracted by the IPFA analysis but the percentage of variance explained is just 6.7%.

The IPFA analysis in summary suggests that, although the innovation literature has been mainly concerned with ‘traditional’ or technological innovations, ‘wider’ or organisational innovations play a predominant role in the innovative activity of UK firms.

Having identified the two factors, in order to identify the existence of clusters of firms based upon the intensity of use of the 7 innovations we have carried out a two-step cluster analysis over the projection of the firms standardized factor scores (the latter being the summary information on the intensity of use of each factor). This has resulted in 3 clusters being identified containing 9317 (cluster 1), 3881 (cluster 2), and 3185 (cluster 3) firms/enterprises respectively. In Figure 2 we report the calculated 95% confidence intervals for the average intensity of use (i.e. the average standardized factor score) of Factor 1 and Factor 2 for each of the three clusters.

[Figure 2 about here]

From Figure 2 one may observe that cluster 1 firms use organisational innovations at levels below the sample average (the average standardised factor score) represented by the straight horizontal line. The other two clusters are made of firms that use organisational innovations progressively more intensively. The same can be said for the differences across the clusters in the second factor illustrating the intensity of use of technological innovations (see Figure 2b) with usage increasing as one moves from cluster 1 through to cluster 3.

Table 8 reports the percentage of the firms within each cluster that have introduced each of the 7 innovations. As predicted by the factor analysis the intensity of use of the practices is highest in cluster 3 where a majority of the firms have adopted each of the 7 innovations. Cluster 1 contains the least ‘innovative’ firms. Within this cluster less than 2% of the firms report having carried out organisational innovative activities, although about 22% have introduced technological innovations. Although not shown, 6% have developed new products but only 2.3% of those products (against 42% in cluster 3) were new to the market rather than just new to the firm.

Interestingly, the extent of technological innovation as measured by MACHINE is comparatively high in each of the three clusters, although its intensity is less than proportional to the extent of overall firm innovativeness. This may confirm that technological innovations can more easily be introduced and assimilated than organisational innovations or a product new to the market, which require flexibility and cognitive skills that not all firms might possess (see Brynjolfsson and Hitt 1994, 2000, Bresnahan et al 2002, Colombo and Delmastro 2002, Black and Lynch 2004, Battisti et al 2005, etc).

[Table 8 about here]

Given that cluster 1 has the largest number of firms and cluster 3 has the smallest, to the extent that the CIS4 is representative of the UK population, this suggests that about 19.4% of the UK firms operate well above average in terms of innovative activity while 56.9% perform below the average.

Interestingly, across the clusters we find that Factor 1 innovation is positively associated with Factor 2 innovation, suggesting that organisational innovations and technological innovations do not represent substitute, alternative or competing innovation strategies, but rather are complements with positive synergistic effects. If the factors had been substitutes we would expect to have seen some firms using organisational innovations intensively but not technological innovations and other firms using technological innovations intensely but not organisational innovations. We do not observe such patterns and thus may reliably adduce that the organisational and technological innovations are complements.

6. INNOVATION AND FIRM CHARACTERISTICS

The theoretical framework we have proposed suggests that in addition to synergistic effects that encourage simultaneous use of innovations, there are many firm specific and environmental effects that can explain differences in the use of technologies across firms in a cross section. We have summarised them in the components of the vector θ_i. Having identified three clusters of firms in the data, in this section we explore apparent associations within the data to the elements of that vector. We are well aware that in a single cross section one cannot imply causality and that the methods that we rely upon thus only indicate association. Positive associations are necessary but not sufficient to showing that the characteristics impact upon use.

The first column of Table 9 reports the average size of the firm in each cluster, measured by the number of employees in 2004. The extent of firm innovativeness seems to increase with firm size, with cluster 1 firms being mostly small (trimmed mean = 76.84; median =27), cluster 2 being mainly medium sized firms (trimmed mean = 140.93; median = 52) and cluster 3 being medium to large firms (trimmed mean = 219.30, median =81.5). However, the standard deviations are very large suggesting that the averages can be highly misrepresentative. In order to visualize the within cluster distribution of firm size, in Figure 3 we group the firms in each cluster into 3 classes: small (10-49 employees), medium (50-249) and large (250 or more). Figure 3 shows that: cluster size compositions are quite heterogeneous; the relative importance of large firms is highest in the third cluster; and the majority of small firms tend to populate the first cluster.

[Figure 3 about here]

We find that the proportion of establishments that carry out in house R&D[11] is lowest in cluster 1 and highest in cluster 3 reflecting the Schumpeterian hypothesis that formalised R&D exerts a positive impact upon the use of an innovation. The proportion of employees with a degree in science and engineering subjects or other subjects both increase progressively from cluster 1 to 3 confirming the importance of the link between innovation and skills emphasised by, among others, Caroli and Van

Reenen, (2001), Bresnahan et. al. (2002). The percentage of firms that received public support increases with the extent of innovative activity carried out by the firm, reaching a peak of 25% in the highly innovative group (cluster 3). The proportion of firms that are part of a group (versus independent establishments) is higher in cluster 3 than in the other clusters. No significant differences across clusters has been found with respect to (i) whether the market for the firm's final product is international or (ii) the age of establishments.

In Table 10 we report the distribution of firms across industrial sectors by clusters. We observe that in every sector Cluster 1 contains the largest number of firms suggesting that the distribution of firm innovativeness is skewed. Secondly, firms operating in the service sector are no more likely to belong to Cluster 3 than firms in other sectors. Thirdly, within the production sector, perhaps unsurprisingly, firms in mining and quarrying, electricity, gas and water supply and construction are the least intensive innovators. By contrast, firms in high technology sectors such as manufacturing of electrical and optical equipments, manufacturing of transport equipments (followed by manufacturing of fuels, chemicals, plastic metals & minerals) are more intensive innovators.

The two sectors with the highest percentage of low intensity users are in services. They are retail trade and hotels and restaurants. These are two sectors previously noted in the literature as exhibiting a particularly wide productivity gap relative to other sectors (see for example Griffith et al. 2003).

[Table 10 about here]

These results are essentially a picture at a moment in time of the innovative state of UK industry where innovation is essentially represented by two factors (one organisational and the other technological) enabling one to divide the population of firms in to three clusters, 1,2, and 3 in which the intensity of use of both factors increases as one moves from cluster 1 through to cluster 3. The analysis suggests that the number of firms in each cluster reduces as one goes through clusters 1 to 3 and that firms in the higher clusters do R&D, employ graduates, receive public support and are in higher tech sectors.

It is not possible with the data at our disposal to consider cause and effect. Thus we are unable to say whether firms are large because they are innovative or innovative because they are large. Similar statements can be made with respect to spending on R&D, employment of graduates and receipt of public support. We are thus unable to say whether only 19.4% of the UK firms operate well above average in terms of innovative activity while 56.9% perform below the average, because of their character or their characters are precisely because they do so perform. The real contribution of this analysis is that the findings relate to both technological and organisational innovations and their use in parallel. Past analysis has concentrated on technological innovation but these results extend to both technological and organisational innovations jointly.

7. INTENSITY OF INNOVATION AND FIRM PERFORMANCE

The impact of firm innovativeness upon firm performance has been the concern of an extensive literature (see for example Hall, 2004). In particular, within the economics of innovation and technological change and within the endogenous growth literature one can find several theoretical and empirical studies that have demonstrated the role played by technological innovations in promoting competitiveness at both micro and macro levels. The evidence on the impact of the adoption of organisational innovations, for a number of reasons, tends to be less consistent (see for example Battisti and Iona, 2006 for a review of the literature on the impact of a range of such practices upon firm performance). In both cases however most of the existing studies tend to analyse the impact of individual innovative practices in isolation. However, if, as claimed in this paper, complementarity effects exist, such an approach can be highly misleading, and only an integrated approach will be able to capture synergistic effects and the (extra) profit generated by joint adoption.

Due to the nature of the CIS4 data and the strong potential endogeneity of several of the variables, we have not been able (or willing) to specify any causal relation in order to explore the relation between innovation and firm performance or to test its statistical significance. However, we have looked at differences in the performance of the companies in the three clusters. In the absence of independent data upon sample firm performance, we measure performance by using indicators available from the responses to the CIS4 questionnaire (although they are mostly based upon a view of innovation as product innovation) to do this. An obvious starter for measuring impact on performance is the impact of innovation upon firm value added. Unfortunately, we do not have direct measures of the value added due to each or any of the innovative activities investigated above[12]. However, CIS4 contains a question (Q1290) on the establishment's own estimate of the effect of the introduction of product and processes in increasing value added. The responses are reported in Table 11 and diagrammatically in Figure 4.

[Figure 4 about here]

The responses to Q1290 clearly show that the largest share of those who reported 'high importance' (44.13%) are in cluster 3 while the largest proportion of the 'not relevant' (54.55%) can be found in the least innovative cluster (1) which is also the largest cluster.

[Table 11 about here]

We have undertaken similar analysis on responses detailing firms' views as to the impact of innovation upon turnover (Q8). These we do not report in detail but the results are similar to the above. Innovation gets to be more important to firms as a determinant of performance as one moves from cluster 1 to cluster 2 to cluster 3 firms.

These results indicate that firms' own view of the importance of innovation as a determinant of firm performance, increases as one moves from clusters 1 to 3. However in the absence of appropriate data one cannot say whether firms are in cluster 3 because innovation is important or whether innovation is important because the firm is in cluster 3. What one can say however is that cluster membership depends upon both technological and organisational innovative behaviour and thus any links are not restricted to technological innovation alone - organisational innovation also matters.

8. INNOVATION PERSISTENCY: EVIDENCE FROM CIS4 AND CIS3

In this section we explore whether firms that are innovative are also continuously innovative. This has two purposes. The first is to explore whether, just as performance may result from multiple innovation rather than isolated individual innovations, so it may be the case that, intertemporally, continuous innovation is required to improve performance rather than isolated instances of innovation. Secondly our data only indicates whether firms introduced particular innovations in the 2002 – 2004 period and does not distinguish within the non-innovator group those who introduced innovations at other times from those who never innovate. Persistency analysis may overcome this problem.

We compare the extent of innovative activity reported by the cohort of firms in the CIS4 (16383 establishments) and the CIS3 (8172 establishments). While CIS4 covers innovative activity carried out between 2002 and 2004, the CIS3 covers innovative activity carried out between 1998 and 2000 (for details see www.berr.gov.uk/files/file9657.pdf.). Due to the nature of the sample design of the two surveys there are only 959 establishments for which we have information in both surveys.[13]

In the first two columns of Table 12 we report the proportion of establishments that have introduced each of the studied innovation in the two time periods (2002-2004 and 1998-2000). This provides us with an overview of the inter-temporal dimension of the intensity of use of each of the 7 innovations under scrutiny. Although the extent of product and process innovation remains significantly unchanged in the two time periods (test statistice for equality of proportions: $z_{PRODINOV}$ = -4.1394 p=0.00 and $z_{PROCINOV}$ = -2.1446 p=.016), the intensity of use of organisational innovations has almost doubled. Also the introduction of "machinery" has increased dramatically but this is likely to be due to the changed definition adopted in the CIS4 which included software and a wider definition of supporting innovative activities which were not previously included in the CIS3 version of the questionnaire[14].

The third column of Table 12 reports the χ^2 test of association between the introduction of an innovation in either, both or neither periods. For all the innovations under scrutiny the test indicates that introduction of an innovation is not independent of introduction in the previous period. This can be better seen in column 4 which reports the proportion of the establishments that introduced the same innovation in the period 2002- 2004 as well as in the period 1998-2000. The degree of persistency of innovative activity is particularly high for organisational innovations. The proportion of establishments that introduced a product or process innovation in both periods is lower.

[Table 12 about here]

9. CONCLUSIONS

Although there exists a large literature on the adoption and diffusion of innovations, only a very limited part considers the joint adoption of a range of innovations. In this study we have used the information contained in the 4th UK Community Innovation Survey (CIS4) to explore the pattern of use of innovations in UK industry and to test for the existence of complementarities among seven types of innovations i.e. process, product, machinery, marketing, organization, management and strategic innovations.

Using a profitability based decision model, by means of statistical and econometric tools we were able to test the existence of complementary effects across the seven innovations. The results suggested widespread synergies among the identified innovations. Decomposition of the payoffs from joint adoption has led us to identify two major sets of innovations. The most important includes the wide or organisational innovative activities (marketing, organization, management and strategic innovations) the second set comprises more traditional or technological activities (machinery, process and product innovations). This finding is of particular importance in that, despite the extensive focus of the innovation literature on technological innovations, ‘wide’ or organizational innovations are found to play a major role in the innovative activity of UK firms. This indicates that innovations based around the technical aspect of the delivery of the final product (either the process, the product per se or the machinery used) although important, tell only part of the story of the innovative effort of a firm.

A two step cluster analysis based upon the intensity of organisational and technological innovative activities was carried out leading to the identification of three clusters of firms, each reflecting the intensity of use of the two sets of innovations. One cluster was found where intensity of adoption of the two sets of innovation was below average. This is the largest cluster containing about 56.9% of the firms in the sample. A second cluster (about 23.7% of the sample) was found with intermediate but above average adoption of both innovative activities. Finally a third cluster (containing about 19.4% of the sample) was found, made up of highly intensive adopters seemingly capable of fully exploiting the synergistic effects generated by joint adoption of organisational and technological innovations.

This is a very new picture of the pattern of innovative activity in the UK economy, simultaneously reflecting both technological and organisational innovations and showing that organisational innovations and technological innovations are complements and not substitutes for each other. The empirical evidence thus suggests that companies that are innovative in one dimension tend to be innovative, although with different intensity, in all dimensions, irrespective of the nature of the innovation.

When looking at the characteristics of the firms populating each cluster we found that the majority of small firms tend to populate the cluster of below average users. We found no significant differences across the three clusters in the percentage of recently established firms**,** but the proportion of establishments that carry out in house R&D, the proportion of enterprises that carry out regular training, the percentage of firms that received public support, the proportion of firms that are part of a group and the proportion of employees with a degree all increase progressively going from cluster 1 to 3 (and therefore with the intensity of use of the two major innovations). The data does not however enable conclusions upon directions of causality.

We found that establishments operating in the service sector are no more or less intensive users of innovations than firms in the production sector. Within the production sector high technology sectors such as manufacturing of electrical and optical equipment, and manufacturing of transport equipments are the sectors with the highest relative number of intensive adopters of new technologies. By contrast, mining and quarrying, electricity, gas and water supply, and construction are the least intensive innovators. Overall the highest percentage of low intensity users are in two service sectors, retail trade and hotels and restaurants. Interestingly these are the same sectors that current literature has found to exhibit a wide productivity gap (see for example Griffith 2003).

In terms of the impact of innovation upon firm performance, due to the lack of a time dimension to the data and the strong potential endogeneity of several of the variables in the CIS4 questionnaire, we cannot explore causality, nor do we have objective data on firm performance indicators. We have thus looked at the establishments' own estimates of the effect of the introduction of product and processes in increasing value added and restrict the analysis to association. Despite this measure being biased toward the technical aspects of innovation, the results clearly show that the largest share of those who reported 'high importance' for impact upon performance (44.13%) are in cluster 3 while the largest proportion of the 'not relevant' to company performance (54.55%) can be found in the least innovative cluster which is also the largest cluster. This does not allow us to say whether firms in the third cluster rank innovation high or because they rank innovation highly they are in the third cluster. However, what we can say is that both technological and organizational innovations are interlinked and any links to performance are not restricted to technological innovations alone: organizational innovations also matters.

In order to investigate whether firms that are innovative are also continuously innovative we have compared the extent of innovative activity reported by the cohort of firms included in both the CIS4 and the earlier CIS3 survey. The findings reinforce a view that intertemporal persistence is important to performance. Although the extent of product and process innovation remains largely unchanged in the two time periods, the intensity of use of organisational innovations has almost doubled.

In terms of contribution, we believe, firstly, that our results make a significant contribution to the mapping of innovation in the UK, simultaneously taking into account of all types of innovation. The complementarity of innovations and the simultaneous introduction of different innovations, suggests that future mapping exercises will need to pay much more attention to synergies and complementarities than has been the case in the past. Secondly, although our finding that that 56.9% of UK firms are in an underperforming low innovation cluster is worrying, the characteristics of firms in that cluster (small, no in house R&D, no regular training, no public support, few graduate employees etc) may indicate where, and on what, innovation policy should be targeted if the innovative performance of these firms is to be improved. Thirdly, the finding that organisational and technological innovations are complements suggests that the theoretical literature that suggests that technological innovation in the absence of organisational innovation alone cannot drive competitiveness has empirical validity and implications for corporate behaviour. Finally the findings suggest that future research on firm innovative behaviour and performance should give greater emphasis to the integration of technological and organisational factors. In a more limited vision, it would also appear that following on from this paper: there are opportunities to, for example, explore other diffusion models based upon information acquisition and uncertainty as alternatives to the profitability based models. More innovation survey data will also soon be available that may well enable better testing of the causal relation between the extent of multi innovation adoption and firm characteristics.

References

Arora A. (1996) ‘Testing for complementarities in reduced-form regressions: A note,’ *Economics Letters*, Elsevier, **50**(1), pp. 51-55.

Arora A. and A. Gambardella (1990) ‘Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology,’ *Journal of Industrial Economics*, Blackwell Publishing, **38**(4), pp 361-79.

Åstebro T. (2002) ‘Non-capital investment costs and the adoption of CAD and CNC in US metalworking industries’, *Rand Journal of Economics*, **33**, pp.672-688.

Astebro, T. (1995), ‘The effect of management and social interaction on the intra firm diffusion of electronic mail systems’, *IEEE Transactions on Engineering Management*, **42** (4), pp 319 –331.

Bartel, A. P. and Lichtenberg, F. R. (1987) ‘The Comparative Advantage of Educated Workers in Implementing New Technology’, *Review of Economics and Statistics*, **69**, pp 1-11.

Battisti G., Mourani G. A., and P. Stoneman (2008) ‘Causality and a firm level Innovation Scoreboard’, *The Economics of Innovation and New technology*- special issue on Corporate R&D, *forthcoming*.

Battisti, G., Canepa, A., Stoneman, P., (2008). ‘The diffusion of e-business activities in the UK: productivity, profitability, externalities and policy’, *Research Policy***,** *forthcoming.*

Battisti G., Colombo M.G., Rabbiosi L. (2005) 'Complementarity effects in the simultaneous diffusion of technological and organisational innovations', WP.05.03 *Quaderni CIRET*, CIRET-Dipartimento di Ingegneria Gestionale, Universita' Politecnico di Milano –Italy, pp 1-32..

Battisti G. and A. Iona (2006) ‘Can management practices explain the UK productivity gap? A review of the evidence from the adoption of management practices’, *Aston Business School Working Paper*, RP number: RP0632

Battisti G. and A. Iona (2007) 'On the adoption decision and the intensity of use of complementary innovations: the intra firm diffusion of management practices across UK establishments', *Aston Business School Working Paper Series*, RP number:RP0722, pp.1-31.

Berman E., Bound J. and Z. Griliches (1994). ‘Changes in the demand for skilled labor within U.S. manufacturing: Evidence from the annual survey of manufactures,’ *Quarterly Journal of Economics*, **109**, pp. 367-97.

Berman E., Bound J. and S. Machin, (1997) ‘Implications of skill-biased technological change: International evidence’, *Centre for Economic Performance Discussion Paper* No. 24.

Black SE, Lynch L. (2004) ‘What's Driving the new economy? The Benefits of Workplace Innovation’, *Economic Journal*, **114** (493), pp. 97-116.

Bloom N. and Van Reenen J. (2007), ’*Measuring and explaining management practices across firms and countries*’, *Quarterly Journal of Economics*, **122** (4), pp. 1351-1408

Bresnahan TF, Brynjolfsson E, Hitt LM. (2002) ‘Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence’. *Quarterly Journal of Economics*, **117** (1), pp. 339-376.

Brynjolfsson E., and Hitt L.M. (1994), ‘Paradox lost? Firm-level evidence of high returns to information systems spending’, MIT Discussion Paper.

Brynjolfsson E., and Hitt L.M. (2000), ‘Beyond computation; information technology, organizational transformation and business performance’, *Journal of Economic Perspectives*, **14** (4).

Cappelli P, Neumark D. (2001) ‘Do ‘High-Performance’ Work Practices Improve Establishment- Level Outcomes?’ *Industrial and Labor Relations Review*, **54**(4), pp. 737-775

Caroli E. and Van Reenen J. (2001), ’Skill-biased organisational change? Evidence from a panel of British and French establishments‘, *The Quarterly Journal of Economics*, **116** (4), pp.1449-1492..

Cohen, W. and D. Levinthal (1989), ‘Innovation and Learning: the Two faces of R&D, *Economic Journal*, **99**, pp.569-96.

Colombo M.G. and M. Delmastro (2002) ‘The determinants of organisational change and structural inertia: Technological and organisational factors”, *Journal of Economics & Management Strategy*, **11**, pp. 595-635.

Colombo M.G. and R. Mosconi (1995) ‘Complementarity and cumulative learning effects in the early diffusion of multiple technologies’, *The Journal of Industrial Economics*, **63**, pp. 13-48.

David P. A. (2003) ‘Zvi Griliches on diffusion, lags and productivity growth ... connecting the dots’, Prepared for the Conference on R&D, Education and Productivity Held in Memory of Zvi Griliches (1930 –1999) 25-27th, August 2003, Carre des Sciences, Ministère de la Recherche Paris, France

Edwards T., Battisti G., and Neely A. (2004), ‘Value creation and the UK economy: A review of strategic options’, *International Journal of Management Reviews*, **5/6** (*3&4)*, pp.191-213.

Finegold, D, Soskice, D.(1988) 'The failure of training in Britain: analysis and prescription', *Oxford Review of Economic Policy,* **4,**: pp. 21-53.

Geroski, P. A., (2000) ‘Models of technology diffusion’, *Research Policy*, Elsevier, **29** (4-5), pp. 603-625, April.

Griffith, R, Harrison, R, Haskel, J and Sako, M (2003), ‘*The UK productivity gap and the importance of the service sectors*’, Advanced Institute of Management (AIM) Briefing Note, December.

Hall, B. (2004), ’Innovation and diffusion‘, *NBER Working Paper* No.10212, NBER, Cambridge Mass.

Hannah T.H. and J.M. McDowell (1984) ’The determinants of technology adoption: The case of the banking firm‘, *Rand Journal of Economics*, **15**, pp. 328-335.

Ichniowski C. and Shaw K. (1995) ’Old dogs and new tricks: Determinants of the adoption of productivity-enhancing work practices’, *Brookings Papers on Economic Activity: Microeconomics*, Spring, pp. 1-65.

Ichniowski, C. Shaw and K. Prennushi, G. (1997), ‘The effects of human resource management practices on productivity: a study of steel finishing lines, *American Economic Review,* **87** (3), pp. 291-313.

Ireland, N., Stoneman, P., 1986. Technological diffusion, expectations and welfare. *Oxford Economic Papers*, **38**, pp. 283-304.

Karshenas M. and P. Stoneman (1993) ‘Rank, stock, order and epidemic effects in the diffusion of new process technologies: An empirical model’, *Rand Journal of Economics*, **24**, pp. 503-28.

Little J. S. and R. K. Triest (1996), ‘Technology Diffusion in U.S. Manufacturing: The Geographic Dimension’ in Fuhrer J.C. and J. S. Little (Ed), *Technology and Growth.* Conference proceedings, Federal Reserve Bank of Boston.

Mansfield E. (1968) ‘*Industrial research and technological innovation’*, New York: W.W. Norton.'

Milgrom, P. and J. Roberts (1990) ‘The economics of modern manufacturing: Technology, strategy, and organisation’, *American Economic Review,* **80**, pp. 511-28.

Milgrom, P. and J. Roberts (1995), ‘Complementarities and Fit: Strategy, Structure, and Organizational Change in Manufacturing”, *Journal of Accounting and Economics*, **19**, pp. 179-208

Noteboom B. (1993), ‘Adoption, Firm Size and Risk of Implementation’, *The Economics of Innovation and New Technology*, **2**, pp. 203-216.

O’Mahony, M and de Boer, W (2002), “Britain’s relative productivity performance: has anything changed?”, *National Institute Economic Review,* January.

Porter, M.E. and Ketels, C.H.M. (2003), ‘UK Competitiveness: moving to the next stage’, *DTI Economics Paper No.3* (May).

Ruigrok W, Pettigrew A, Peck S and Whittington R, (1999) ‘Corporate Restructuring and New Forms of Organizing: Evidence from Europe’, *Management International Review*, Special Issue,**199** (2), pp 41 – 64.

Saloner G. and Shephard A. (1995), ‘Adoption of Technologies with Network Effects: an Empirical Examination of the Adoption of Automated Teller Machines’, *Rand Journal of Economics*, **26** (3), pp. 479-501.

Stoneman P (2002) ‘*The Economics of Technological Diffusion’*. Oxford: Blackwell Publishers.

Stoneman P. (2004), ‘Path Dependency and Reswitching in a model of Multi - Technology Adoption’ in Guinnane T, Sundstrom W and W. Whatley (eds.), *History Matters: Essays on Economic Growth, Technology and Demographic Change*, Stanford University Press, pp.36 – 62.

Stoneman P. and G. Battisti (2008) 'The Diffusion of New Technology ' Chapter 3 of Part IV of Bronwyn H Hall and Nathan Rosenberg (eds.)'*Handbook of the Economics of Technical Change*' North Holland, Elsevier, forthcoming.

Whittington R, Pettigrew A., Peck S., Fenton. E. and M. Conyon (1999): 'Change and Complementarities in the New Competitive Landscape: A European Panel Study, 1992 - 1996', *Organisation Science*, **10** (5), pp. 583-600

Wengel J, Nylund, A, Sjogren, L. B., Stoneman P.,L., Bellini, N. Bonaccorsi, A., and Shapira. P., (2000), *Surveying Organisational Innovation on a European Level – Challenges and Options*, a Report to the CIS, DG XIII–C of the European Commission, April.

APPENDIX 1: 1992 SIC CODES BY WIDE INDUSTRY GROUPING.

CODE	*Industry*
10	Mining of Coal
11	Extraction of Oil and Gas
14	Other Mining and Quarrying
15	Food & Beverages
16	Tobacco
17	Textiles
18	Clothes
19	Leather
20	Wood
21	Paper
22	Publishing
23	Coke, Petroleum & Nuclear Fuel
24	Chemicals
25	Rubber and Plastic
26	Other Non-Metallic Mineral Products
27	Basic Metals
28	Fabricated Metal Products
29	Machinery and Equipment
30	Office Machinery and Computers
31	Electrical Machinery
32	Radio, Television & Communication
33	Medical / Optical Instruments
34	Motor Vehicles
35	Other Transport
36	Furniture
37	Recycling
40	Electricity, Gas and Water Supply
41	Collection, Purification & Distribution of Water
45	Construction
51	Wholesale
60	Land Transport
61	Water Transport
62	Air Transport

64 Post & Telecommunications

65 Financial Intermediation
66 Insurance & Pensions
67 Financial Intermediation (Activities Auxiliary)

70 Real Estate
71 Renting of Machinery and Equipment
72 Computer & Related Activities
73 Research & Development
74 Business Activities

Table 1. Definition of Innovation variables and sample adoption (%)

Innovation Variable label	Definition	Adopting firms %
PROCINOV	Whether a product innovation (new to the enterprise or to the market or a significantly improved good or service) has been introduced on the market between 2002-2004: (see Q7-Q8).	20%
PRODINOV	Whether a process innovation (new to the enterprise or to the market that significantly improved methods for the production or supply of goods and services) has been introduced between 2002-2004: (see Q11).	29%
MACHINE	Whether advanced machinery, equipment and computer hardware or software to produce new or significantly improved goods, services, production processes, or delivery methods has been acquired between 2002-2004: (see Q13).	47%
STRATEGY	Whether a new or significantly changed corporate strategy has been implemented between 2002-2004 (see Q23.10).	19.9%
MANAGEMENT	Whether advanced management techniques e.g. knowledge management systems, Investors in People etc has been implemented between 2002-2004 (see Q23.20).	17.6%
ORGANIZATION	Whether major changes to the organisational structure, e.g. introduction of cross-functional teams, outsourcing of major business functions have been implemented between 2002-2004 (see Q23.30).	22.6%
MARKETING	Whether changes in marketing concepts or strategies, e.g. packaging or presentational changes to a product to target new markets, new support services to open up new markets etc. have been implemented between 2002-2004 (see Q23.40).	23%

Table 2. Correlation Matrix Kendall's tau_b correlation coefficient (N=15657)

	Prodinov	Procinov	Machinery	Strategy	Management	Organiz	Marketing
Prodinov	1.000						
Procinov	0.429	1.000					
Machinery	0.319	0.360	1.000				
Strategy	0.275	0.253	0.198	1.000			
Management	0.214	0.238	0.220	0.407	1.000		
Organiz	0.275	0.255	0.204	0.543	0.412	1.000	
Marketing	0.338	0.293	0.252	0.448	0.381	0.445	1.000

Table 3. Control variables, conditional adoption probabilities

Label	**Definition**
SIZE	Number of employees
GROUP	Whether part of a group (1) or independent establishment (0)
INTERNAT	Whether the market is international (1=yes; 0 = no)
AGE	Whether established after 2000 (1=yes; 0=no)
R&D	Whether the enterprise engages in R&D activities (1=yes;0=no)
SCDEGREE	Percentage of the enterprise’s employees educated to degree level or above in Science and Engineering subjects
OTHDEGREE	Percentage of the enterprise’s employees educated to degree level or above in other subjects.
SUPPORTPU	Whether received any public financial support (1=yes; 0=no)
SIC_j	Industry to which the establishment belongs; j=1 to 14,wide SIC92 classification, dummy variables.

Table 4. Control factors and the probability of adoption, probit estimates.

	PROCINOV	PRODINOV	MACHINERY	STRATEGY	MANAGEMENT	ORGANIZ	MARKETING
	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
ONE	**-1.274**	**-0.972**	**-0.630**	**-1.329**	**-1.271**	**-1.311**	**-1.244**
GROUP	**0.208**	**0.236**	**0.042***	**0.370**	**0.300**	**0.491**	**0.282**
INTERNAT	-0.027	0.005	**0.148**	0.060	0.019	0.060	**0.178**
AGE2000	-0.001	**0.073**	-0.019	**0.213**	-0.040	**0.086**	**0.065**
RD	**0.807**	**1.135**	**0.953**	**0.604**	**0.568**	**0.624**	**0.813**
SCDEGREE	0.001	**0.001**	-0.001	**0.001**	0.000	**0.001**	0.001
OTHDEGRE	**0.001**	**0.002**	**0.001***	**0.002**	**0.001**	**0.002**	**0.002**
SUPPORTP	**0.522**	**0.616**	**0.396**	**0.387**	**0.384**	**0.310**	**0.404**
EMPLOYME	**0.000**	**0.000**	0.000	**0.000**	**0.000**	**0.000**	**0.000**
D1	-0.084	**-0.773**	0.020	-0.042	-0.150	-0.102	**-0.465**
D2	**0.170**	**-0.110**	**0.323**	**-0.151**	**-0.235**	**-0.133**	**-0.122**
D3	0.077	-0.054	**0.228**	**-0.160**	**-0.153**	-0.092	**-0.321**
D4	0.060	**0.192**	**0.154**	-0.085	**-0.219**	0.064	**-0.227**
D5	0.056	-0.016	**0.224**	-0.071	-0.088	0.098	**-0.453**
D6	0.010	-0.017	**0.227**	**-0.185**	**-0.284**	-0.126	**-0.234**
D8	**-0.367**	**-0.469**	-0.031	**-0.163**	0.082	-0.105	**-0.323**
D10	**-0.272**	**-0.417**	**-0.231**	**-0.272**	**-0.328**	**-0.317**	**-0.276**
D11	**-0.406**	**-0.523**	**-0.287**	**-0.355**	**-0.178**	**-0.337**	**-0.355**
D12	-0.078	**-0.186**	**0.190**	-0.121	**-0.124**	-0.092	**-0.219**
D13	**0.234**	-0.084	**0.156**	**0.236**	0.028	0.261	0.072
D14	**0.184**	**-0.109**	0.013	0.075	0.056	0.122	-0.087

*coefficients significant at 5% in bold

Table 5. Non-parametric Kendall's tau_b correlations of the residuals[a]

	R_Process	R_Product	R_Machinery	R_Strategy	R_Management	R_Organizat	R_Marketing
R_Process	1.000	0.161	0.131	0.212	0.178	0.192	0.253
R_Product	0.161	1.000	0.297	0.070	0.025	0.106	0.140
R_Machinery	0.131	0.297	1.000	*0.015**	0.027	0.055	0.070
R_Strategy	0.212	0.070	0.015	1.000	0.377	0.489	0.392
R_Management	0.178	0.025	0.027	0.377	1.000	0.329	0.296
R_Organizat	0.192	0.106	0.055	0.489	0.329	1.000	0.422
R_Marketing	0.253	0.140	0.070	0.392	0.296	0.422	1.000

* Correlation is NOT significant at the 0.01 level (p=0.0067).

a Listwise N = 15082

Table 6. Tetrachoric correlations (obs = 15657)

	prodinov	procinov	machinery	strategy	managem	organiz	marketing
prodinov	1.0000						
procinov	0.6643	1.0000					
machinery	0.5033	0.6116	1.0000				
strategy	0.4617	0.4378	0.3497	1.0000			
management	0.3773	0.4212	0.4000	0.6503	1.0000		
organiz	0.4540	0.4359	0.3500	0.7864	0.6547	1.0000	
marketing|	0.5412	0.4896	0.4266	0.6886	0.6174	0.6792	1.0000

Note. All coefficients are significant at 5%.

Table 7. Rotated Factor Loadings

Variable	Factor1	Factor2	Uniqueness
prodinov	0.3300	**0.6778**	0.4316
procinov	0.2477	**0.8514**	0.2137
machinery	0.2390	**0.6439**	0.5283
strategy	**0.8442**	0.2577	0.2209
management	**0.6884**	0.2950	0.4391
organiz	**0.8422**	0.2539	0.2262
marketing	**0.6997**	0.4044|	0.3470
%var	83.5% (57% R)	16.5% (43% R)	

Table 8. Within cluster percentage of firms who report having introduced the innovations

	Managem	**Strategy**	**Organiz**	**Marketing**	**Prodinov**	**Procinov**	**Machine**
Cluster 1	1.5	1.2	2.0	1.6	6.0	1.3	22.3
Cluster 2	18.7	20.7	25.8	27.8	48.2	32.4	71.5
Cluster 3	59.2	69.0	73.5	74.9	76.1	62.9	84.1

Table 9. Firm characteristics by cluster: descriptive statistics

	Size (employees)	Age (whether est. after 2000)	R&D	Training	% with science degree	% with other degree	Part of a group	Public financial support	Internat market for its product	Service sector
CLUSTER 1										
Mean	**168.75***	**0.15**	**0.12**	**0.21**	**2.88***	**4.93***	**0.26**	**0.04**	**0.98**	**0.62**
5% Trimmed mean	76.84	0.11	0.08	0.18	0.88	2.11	0.24	0	1	0.63
Median	27	0	0	0	0	0	0	0	1	1
St. dev.	756.15	0.36	0.33	0.41	11.03	14.60	0.44	0.19	0.13	0.5
Min	9	0	0	0	0	0	0	0	0	0
Max	32655	1	1	1	100	100	1	1	1	1
CLUSTER 2										
Mean	**304.39***	**0.14**	**0.46**	**0.58**	**7.34***	**8.90***	**0.41**	**0.14**	**0.98**	**0.55**
5% Trimmed mean	140.93	0.10	0.46	0.59	4.18	5.82	0.40	0.10	1	0.56
Median	52	0	0	1	0	2	0	0	1	1
St. dev.	1281.23	0.35	0.50	0.49	17.06	17.78	0.49	0.35	0.15	0.50
Min	10	0	0	0	0	0	0	0	0	0
Max	48387	1	1	1	100	100	1	1	1	1
CLUSTER 3										
Mean	**470.68***	**0.16**	**0.68**	**0.76**	**11.00***	**11.46***	**0.53**	**0.25**	**0.97**	**0.55**
5% Trimmed mean	219.30	0.12	0.70	0.79	7.71	8.28	0.53	0.22	1	0.56
Median	81.5	0	1	1	2	5	1	0	1	1
St. dev.	2148.33	0.37	0.47	0.43	20.52	19.34	0.50	0.43	0.17	0.50
Min	10	0	0	0	0	0	0	0	0	0
Max	60498	1	1	1	100	100	1	1	1	1

Table 10. Distribution of firms (%) across sectors by clusters

SIC Classification	**Definition**	**Cluster 1**	**Cluster 2**	**Cluster 3**	*Total (count)*
Production					
10-14	Mining and quarrying	60.9	24.4	14.7	(197)
15-22	Mfr of food, clothing, wood, paper, publish & print	48.6	28.8	22.6	(1432)
23-29	Mfr of fuels, chemicals, plastic metals & minerals	48.6	27.7	23.7	(1897
30-33	Mfr of electrical and optical equipments	34.8	31.7	33.5	(663)
34-35	Mfr of transport equipments	44.5	27.4	28.1	(402)
36-37	Mfr not elsewhere classified	47.4	30.3	22.3	(515)
40-41	Electricity, gas & water supply	68.6	20.0	11.4	(35)
45	Construction	72.9	17.0	10.1	(1603)
Services					
50-51	Wholesale Trade (including cars & bikes)	59.6	23.7	16.7	(1341)
52	Retail Trade (excluding cars & bikes)	73.6	17.4	9.1	(1543)
55	Hotels & restaurants	74.9	15.7	9.5	(983)
60-64	Transport, storage & communication	63.3	21.2	15.5	(1386)
65-67	Financial intermediation	44.6	24.4	31.0	(668)
70-74	Real estate, renting & business activities	50.8	25.3	23.9	(3718)
Total		*56.9*	*23.7*	*19.4*	*(16383)*

Table 11. Degree of importance of product and process innovation in generating Value Added: within cluster composition (column %).

	Cluster 1	**Cluster 2**	**Cluster 3**
Not relevant	**54.55**	19.75	7.09
Low	11.49	13.23	9.84
Medium	22.50	**38.38**	**38.94**
High	11.46	**28.64**	**44.13**
Total	100.00	100.00	100.00
Total (count)	***8178***	***3817***	***3159***

Table 12. Degree of persistency of innovative activity: CIS3-CIS4 panel (proportions)

	Proportion of innovators in CIS4 (1)	**Proportion of innovators in CIS3** (2)	**Test of association $X^2_{v=1}$ (p-value)** (3)	**Proportion of CIS4 innovators that introduced the same innovation also in CIS3** (4)	**Establishments that introduced no innovation in either CIS3 or CIS4** (5)
Prodinov	0.30	0.39	80.24 (0.000)	0.46	0.50
Procinov	0.25	0.30	49.09 (0.000)	0.41	0.57
Machinery[a]	0.72[a]	0.57[a]	4.68 (0.030)	0.75	0.12
Strategy	0.57	0.26	9.44 (0.002)	0.66	0.34
Management	0.47	0.25	20.57 (0.000)	0.61	0.42
Organiz	0.56	0.33	53.63 (0.000)	0.73	0.35
Marketing	0.57	0.29	19.21 (0.000)	0.69	0.33

NOTE: [a] The two proportions cannot be compared as the variable's definition in the CIS3 has been changed in the CIS4 survey.

Figure 1 . Rotated factor loadings

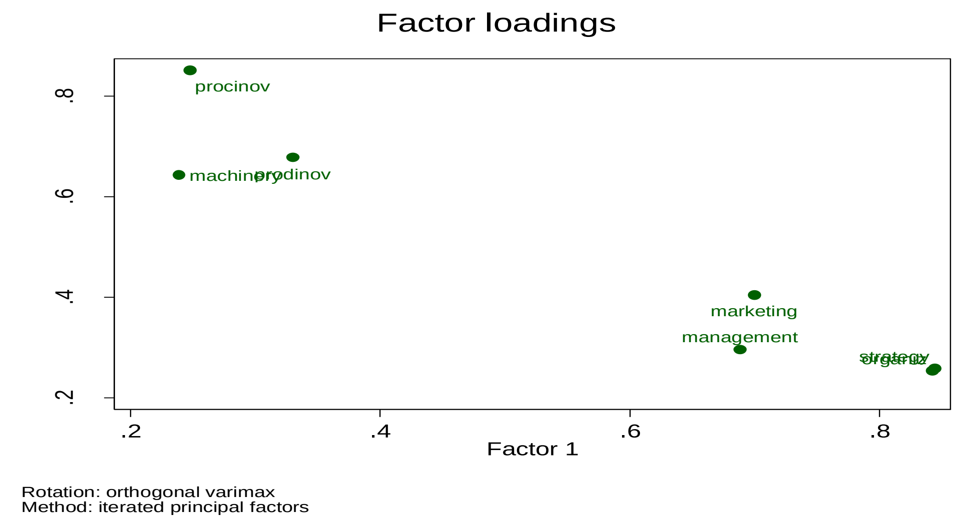


Figure 2. Confidence intervals for the mean of Factor 1 (on the left) and Factor 2 (on the right)

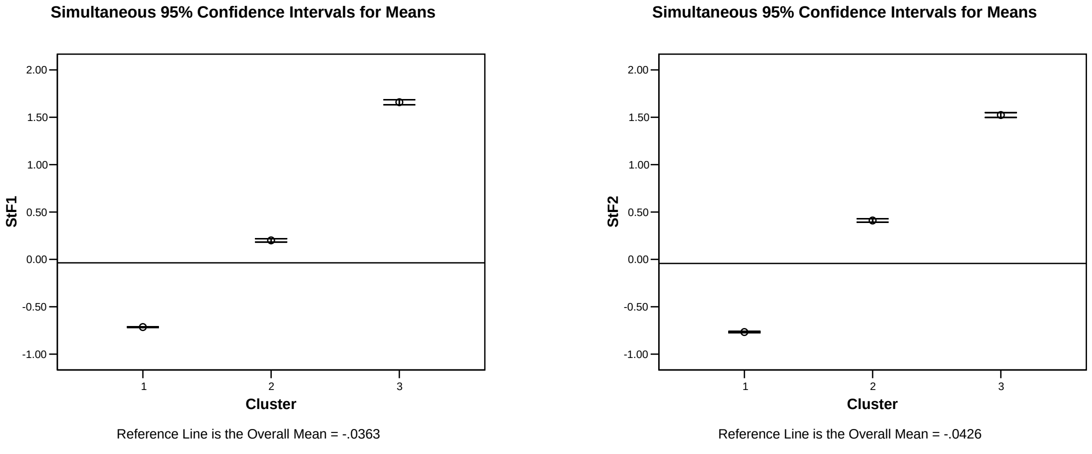


Figure 3. Intra-cluster firm size composition

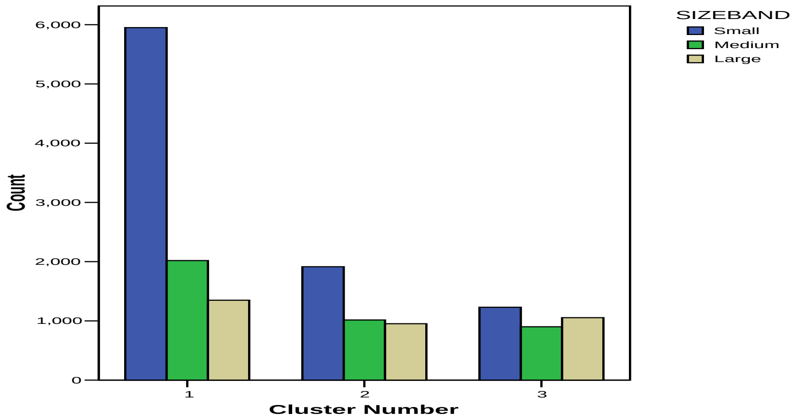
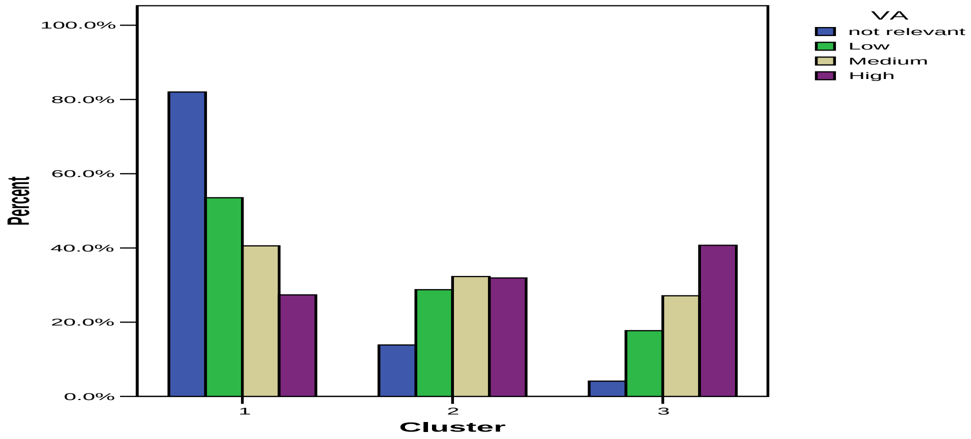


Figure 4. Inter cluster distribution of the degree of importance of product and process innovation in generating VA.



[1] For the provision of which we would like to thank the Department of Trade and Industry (DTI), recently relabelled the Department for Business Enterprise and Regulatory Reform (BERR).

[2] There is some confusion over nomenclature, in that BERR now label the UK CIS4 as the 2006 UK Innovation Survey.

[3] In the UK another Innovation Survey (labelled the 2007 UK Innovation Survey) with results expected mid 2008 has now been carried out, only two years after the CIS 4 exercise, so the four year timing is not adhered to strictly.

[4] Further details upon the UK CIS4 including the questionnaire, the data collection process, sampling, the extraordinarily high response rate, etc. can be found elsewhere see http://www.berr.gov.uk/innovation/innovation-statistics/cis/cis4-sample/page11777.html

[5] In such a case the number of users of the technology y, M(t) at time t, will be given by $M(t) = N(1 - F(c_t(y) + e_{it})$, and be related to the distribution of returns across the N firms, the firm specific costs and the cost of acquisition.

[6] Once again the cross section nature of our data makes it unnecessary to ask what would happen if j and k became available at different times for our data does not reveal intertemporal differences between firms in the pattern of adoption).

[7] A lurking factor is a factor highly correlated with each innovation so that an increase (decrease) in its level increases (decreases) the adoption of each of the two innovations without the two innovations being necessarily complementary.

[8] We also experimented with other firm specific variables present in the dataset such as a dummy reflecting export activity and therefore competitive pressures but this considerably reduced the sample size.

[9]The extraction of principal components amounts to a *variance maximizing (varimax) rotation* of the original variable space. The rotated factor loadings, by stretching the loadings to their extremes (+1 or -1) improve the interpretative capability of the factors, without changing their nature or that of the model.

[10] A very high uniqueness can indicate that a variable may not belong with any of the factors. Uniqueness is 1-communality where communality reflects the common variance in the data structure, i.e. 56.8% of the variance associated with PRODINOV is common, or shared variance

[11] One might argue that R&D be included among the 7 innovations under scrutiny. We decided not to go down that route as we wanted to concentrate on innovation outputs and not on innovation inputs.

[12] Moreover, even if we did the nature of the dataset is such that it would be difficult to establish the direction of the casual relations between adoption timing and payoff from adoption.

[13] We have tried to build a panel merging the information in the CIS2, CIS3 and CIS4. Unfortunately this reduces the sample to 101 establishments making any statistical analysis totally unrepresentative of the UK establishments population.

[14] In CIS4 the relevant question is Question 13.30 on whether in the three year period 2002-2004 the enterprise engaged in the following activity: ' *Acquisition of advanced machinery, equipment and computer hardware or software to produce new or significantly improved goods, services, production processes or delivery methods*'. In the CIS3 similar information was asked in question 9.1 where it was asked whether in 2000 the enterprise engaged in the following activity: '*Acquisition of machinery and equipment (including computer hardware) in connection with process or product innovation'.* Also the response rates for the two questions were different. 939 responses were recorded in the CIS4 round while only 459 in the CIS3 round. Slightly different definitions were given in the 4 questions concerning the introduction of wider innovations (e.g. examples of practices especially in organizational and management innovations) during the three year period preceding the survey. However, in the context of this study we do not see these changes as particularly significant or impeding the comparison over time.