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ICT, Skills, and Organisational Change: Evidence from a Panel of Italian Manufacturing Firms

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ICT, Skills and Organisational Change: evidence from Italian manufacturing firms•

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Abstract

This paper explores how firms' skills and organizational change affect the returns from investments in ICT. Our work contributes to the literature by testing the hypothesis of complementarity in a panel of 540 Italian manufacturing firms during 1995-2000. By drawing on different statistical methods, we do not find any clearcut support to the hypothesis of full complementarity among ICT, human capital and organizational change. We find a strong support to the hypotheses of skill-biased technical change and a weaker support to the skill-biased organizational change hypothesis particularly in medium-sized firms. Our findings suggest that the productivity gains from investments in the three innovative activities are related to firm size.

Keywords: Organizational change, ICT investment, skills, human capital, productivity, complementarity, SMEs
JEL codes: O30, D24, L23

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1. Introduction

This paper explores the organizational and economic implications of the adoption of ICT (information and communication technologies) at the firm level. More precisely, we explore the relationships between the adoption of ICT, skills and organizational change and the implications of different adoption strategies for firms' productivity.

Earlier studies on the demand for skilled labour and productivity growth have primarily focused either on skill-biased technical change (SBTC) or skill-biased organizational change (SBOC). Recently the empirical literature has started to analyse the increasing relative demand for skilled labour in the broad context of corporate change by looking at the labour and productivity implications of both technical and organizational change (Bresnahan, 1999; Bresnahan *et al*., 2002; and a recent survey by Arvanitis, 2005).

The literature has addressed the issue of complementarity by relying on data at different levels of aggregation – countries, industries, and firms. There are also several studies that have tried to test the SBTC hypothesis focusing on the complementarity that occurs at the individual level, analysing the relationship between computers and the human capital of computer users. Each level of analysis has its own advantages and drawbacks. While industry-level or country-level data do not capture important sources of variance across firms, studies centred on individual workers have other important disadvantages. These studies miss an important dimension of the complementarity story represented by organizational changes which take place at the firm level. As Bresnahan (1999) has noticed, "the complementarity between ICT and highly skilled workers – of which there is a plenty – arises more at the level of the firm than the worker" (p. 391).

Recognizing the role of organizational change implies that one accounts for both direct and indirect effects of new technologies on labour demand. Direct effects arise from adoption of skilled labour that is required by the use of new technologies (e.g., computer skills). Indirect effects are spurred by organizational co-inventions and product or services innovations that increase the economic gains of skilled labour. The association between skills and ICT adoption is then mediated by important organizational changes that produce further effects on the relative demand for skills and on the wage inequality at the firm level. The use of ICT increases the volume of data elaboration and transactions within the firm and across firms. This in turn gives rise to modifications in the organization of the firm and calls for analytic, cognitive skills (e.g., marketing analysis and quality control data analysis). Moreover, the use of ICT spurs decentralization of authority and more flexible forms of division of labour such as teamwork, multi-tasking, job rotation, just-in-time, and quality circles. Workers have to deal with greater autonomy, responsibility and uncertainty. This requires both cognitive skills and 'people' skills that are important for interacting and communicating with colleagues, customers and suppliers. To account for the multiple interactions among ICT, skills and organizational change Bresnahan (1999) has introduced the concept of *organizational complementarity* between ICT and highly skilled workers.

The interdependence between concurrent inventions (new forms of work organization and human capital) imposes significant adjustment costs which vary across different ICT adopters. It is likely then that in the short term different firms will have different combinations of co-inventions. And, because of complementarity, firms that have managed to adapt their organization to ICT will enjoy significant *productivity* gains from ICT investments. The existing literature has mainly tested this hypothesis on large firms or in samples where large and smaller firms are pooled together. However, the organizational peculiarities of large firms relative to SMEs calls for a deeper understanding of productivity gains of ICT investments, skills, and organizational change which we expect to be different across firms' size classes.

Several earlier empirical works on complementarity share three methodological problems: the simultaneity of intra-firm processes, the presence of firms' unobserved heterogeneity, and the measurement of productivity effects arising from the joint adoption of more than two innovative activities. In this paper we test the theory of complementarity between ICT, skills and organizational change in a panel of 540 Italian manufacturing firms over the years 1995 to 2000. We tried to account for the problems mentioned above by adopting several estimation methods.

Following earlier studies of the SBTC and the SBOC hypotheses, we use two approaches for studying the complementarity in the context of the production function. One is based on the analysis of the productivity effects of pair-wise interactions between ICT, human capital and organizational change (e.g., Bresnahan *et al*., 2002; Caroli and van Reenen, 2001). We used lagged values of independent variables to moderate the problem of simultaneity and estimated a production equation with variables in differences to deal with time-invariant unobserved heterogeneity. We have also estimated a production equation with a treatment effect model to account for possible sample selection of the decision variables.

The other approach accounts for the complexity of interactions among three innovation activities by introducing different clusters of activities in the production function (Athey and Stern, 1998; Arvanitis, 2005). These clusters identify different groups of firms - from the most ‘traditional’ one (no adoption of ICT, no organizational innovations and limited investments in human capital) to the ‘innovative’ firm, which ranks high on the scale of all the complements. The latter group corresponds to the ‘modern’ firm, which takes advantage of modular production systems (Milgrom and Roberts, 1990; Baldwin and Clark, 1997).

This paper contributes to the literature on the following grounds. First, unlike earlier studies that have mostly focused on large firms, we have explored the issue of complementarity also in small and medium firms. To our knowledge, there is only sparse evidence about the impact of educated personnel on the adoption of ICTs in Italian SMEs (e.g., Lucchetti and Sterlacchini, 2004). It also remains quite unexplored the problem of multiple interactions among firm size, skills, adoption of ICTs, and reorganization of business processes (Fabiani *et al.*, 2005). Moreover, the few studies of which we are aware do not examine the implications of these interactions for firms’ productivity.

Second, we provide novel empirical evidence on Italian manufacturing firms. Earlier studies on different European countries have mostly focused on either the SBTC hypothesis or the SBOC hypothesis (e.g., Caroli and Van Reenen, 2001; Piva et al., 2005) while only few have addressed the issue of complementarity among ICT, human capital and organizational change (Arvanitis, 2005). We test the hypothesis of "organizational complementarity" between ICT and skills in a production function framework and look at the differences between large firms and SMEs.

Our results show that large, medium and small firms have different patterns of adoption of (and different productivity gains from) skills, ICTs and especially organizational change. Our findings do not provide any evidence in favour of the hypothesis of complementarity between ICT, human capital and organizational change (*organizational complementarity*) in firms of different size classes. Instead, our results support the hypotheses of pair-wise complementarity (SBTC and SBOC) especially in medium sized firms.

This paper is organized as follows. Section 2 summarizes the main findings in the literature; Section 3 describes the methodology. Section 4 describes the data and variables used in the empirical analysis. Section 5 reports and discusses the results and Section 6 concludes.

2. Background literature

This paper draws on three streams of the literature that address the following issues: skill-biased technical change (SBTC), skill-biased organisational change (SBOC) and the organizational complementarity between ICT and skills. Recent empirical works on the *complementarity* among ICT investments, human capital investments and organizational change and their effects on firms' productivity (Bresnahan *et al*. 2002; Caroli and Van Reenen; 2001) draw on the theory of modern manufacturing, which points out the supermodularity of the production function arising from the adoption of new technologies and new forms of division of labour that depart from the mass production and bureaucratic, centralized organization (Milgrom and Roberts 1990, 1995).

Skill-biased technical change

According to the *skill-biased technical change* (SBTC) hypothesis technological change, and particularly the adoption of ICTs, increases the demand for skilled labour with respect to unskilled labour and leads to increasing wage inequality (Machin and Van Reenen, 1998; Autor, Katz and Krueger, 1998; Acemoglu, 1998). The use of computer-based technologies induces an increasing demand for skilled labour relative to manual, unskilled workers. And this, together with a slow adaptation of skilled labour supply, determines an increase in wage dispersion. This hypothesis is supported by the fact that the demand for skills and the skill premium appear to increase within plants and industries, rather than being associated with labour relocation towards specific sectors (e.g., services) (Berman *et al*., 1994)[1]. However, skill-biased technical change is particularly significant in industries such as office machines, electrical machinery, printing, and publishing. Together they account for 40% of within-industry increase in the relative demand for skills in a sample of OECD countries (Berman *et al*., 1997).

ICTs are a general-purpose technology (GPT) or a new technological paradigm. As such they induce major changes in the system of production and institutional settings (Dosi, 1982; Freeman and Perez, 1986; Bresnahan, and Trajtenberg, 1995; David and Wright, 1999; Aghion, 2002). Users and producers need a long time to experiment with these new technologies and adapt their organizations to the new system of production. The supply of skills required by the new technologies and methods of production also takes time to materialize and this gives rise to disequilibrium in the labour market. The overall impact of GPTs then is not direct but takes place through a series of secondary innovations and the adjustment process is characterized by periods of increasing skill premium and productivity slowdown.

The skill-biased technical change hypothesis has been supported by several studies that employed different measures of technological change (R&D investments, ICT expenditures, adoption of new technologies, introduction of industrial innovations), and used both cross-sectional or longitudinal samples from different countries (see Piva and Vivarelli, 2004, for a survey).

In the case of Italy, the empirical evidence shows the rising importance of skilled workers associated to technological change. For instance, Manacorda (1996) measured the shift in demand for skills relative to its supply. Drawing on data from the Bank of Italy's *Survey of Household Income and Wealth* for the period 1977-1993, Manacorda shows that net demand for skilled workers has increased significantly, especially in North Italy. Moreover, looking at one of the manufacturing activities most intensive of unskilled labour, the metal-manufacturing sector, Erickson and Ichino (1994) found that the proportion of blue collars decreased from 75.8 to 63.5 percent of the total labour force during the period 1976-1991. This body of evidence lends support to the hypothesis of within sectors technological shifts toward more skill-intensive production, even if it could also be the result of internal promotion, which is a form of wage drift. Casavola *et al.* (1996) explore more directly the labour demand effects of technical change at the firm level. The firm's share of "intangible assets" (i.e., R&D expenditures, patents and licenses, and marketing expenditures) in the total capital stock is used as a proxy for the use of new technologies by the firm.[2] The results obtained by Casavola *et al*. indicate that technologically advanced firms pay a higher premium to white-collar workers. The same firms employ a comparatively higher share of white-collar staff. The authors also show that the increase in earnings dispersion appears to be more marked among small firms. Although they do not explain this result, we suppose that it is probably due to their greater flexibility in wage setting compared with larger firms. Their cross-section and panel estimates (with firms' fixed effects and time-variant industry and location effects) show that innovation has a positive and significant impact on the employment ratio and the wage shares ratio (i.e., the ratio between total wages to white collars over total wages to blue collars). In the absence of a direct measure of skills, Casavola *et al*. use firms' fixed effects as a proxy for the average 'ability' of the work force in each firm. The regression with firms' fixed-effect yields similar results[3]. More recently, Bratti and Matteucci

(2004) have tested the SBTC hypothesis by using data from the Italian manufacturing. They have analyzed the impact of ICT and R&D expenditures on the shares of production and non-production workers and found a strong, generalized effect for non-production workers only. These results are in line with the hypothesis of new technologies as a substitute for unskilled workers, while they provide only limited support to the hypothesis of complementarity between ICT and skills.

Skill- biased organizational change

Another implication of the economics of the modern manufacturing is that organizational changes taking place at the firm level produce a further shock to the relative demand for skills and wage inequality. This is in brief the *skill-biased organizational change hypothesis* (SBOC). The main argument of the SBOC hypothesis is that the adoption of new organizational systems based on decentralized decision-making and delayering calls for more skilled people. Because of the complementarity between new organizational systems and skilled labour firms that adopt the two complements are expected to outperform firms that use only one of them. Caroli and Van Reenen (2001) compare the benefits and costs of new, decentralized organizations. The benefits are represented by the reduction of the cost of information transfer and communication, a greater reactivity of firms to external changes due to the presence of more generalist with respect to specialist people, the reduction of the cost of monitoring activities and the increase in job satisfaction due to job enrichment, i.e., a greater involvement in problem solving, higher information sharing and participation in decision making. The costs of decentralization arise from higher risk of duplication of information, increased probability of mistakes due to a lower level of control, reduced returns to specialization and reduced worker efficiency associated with greater stress. The SBOC theory predicts that skills raise the benefits and reduce the costs of decentralization of responsibility within organizations; therefore skill-intensive firms, which introduce organizational changes, will have greater productivity gains than non skill-intensive firms. This is because skilled workers have a greater ability to handle information, communicate and interact with other people; they also tend to be more autonomous and more satisfied with their job.

Empirical evidence from different countries (especially France and the US) lends support to the SBOC hypothesis (see Piva *et al.*, 2005, for a review).

Recent studies on Italian data report on both skill-biased technical and organizational change. For example, Piva and Vivarelli (2004) adopt a seemingly unrelated regression model (SUR) with fixed effects to test the hypothesis of skill biased technical change and skill biased organizational change. These authors rely on a panel of 488 Italian manufacturing firms in the period 1989-1997. Their analysis, based on R&D as a measure of technical change, does not provide support to the hypothesis of skill-biased technical change. Instead, their findings suggest that only organizational change has a significant marginal effect on the demand for skills. Drawing on the same dataset, Piva et al (2005) also found that the interaction of R&D and organizational change yields a significant effect on the share of white collars (a proxy for skilled labour) and a negative effect on the share of blue collars. This evidence appears to be in line with SBOC hypothesis and also suggests that the interactions among technical change, organizational change and skills are complex and difficult to measure.

Complementarity among ICT, skills and organizational change

As argued by Bresnahan (1999), SBTC and SBOC hypotheses are the two sides of the same coin. Drawing on the mixed empirical evidence reported in studies that have tried to test the SBTC, Bresnahan introduces the concept of *organizational complementarity* between ICT and skilled labour. In this perspective, technological and organizational change together call for more skilled labour for several reasons. First, there is limited substitution of computers for human work. The substitution is apparent for simple tasks not requiring further processing like record keeping or computation, which are normally carried out by less skilled people. For more complex and cognitive work, typically carried out by more highly skilled managers and professionals, the automation of tasks and substitution by computers is more difficult. Standardization and automation of repetitive procedures allow for a greater centralisation of data and information management; they also require new tasks in the organizations: from functional or specialist tasks to more generalist, problem-solving roles that imply more autonomy and responsibility. A greater amount of information produced and transmitted within the organization and across organizations also calls for additional cognitive, analytical skills (e.g., marketing analysts) and interactive or people skills.

Second, the use of computing, especially 'organizational computing' is mostly important in service-intensive activities - the service sector and the office departments of manufacturing firms.[4] The increase in the relative demand for skilled people is therefore more likely to occur in these activities than in manufacturing ones. However, many manufacturing firms adopt applications like enterprise resource planning (ERP), material requirements planning (MRP) and database management systems (DBMS), which call for significant organizational changes and skilled labour. Moreover, many manufacturing firms are adopting new computer-based systems for supply chain and customer relationship management, which call for cognitive and people skills (Clark, 2003).

Bresnahan *et al*. (2002) test the hypothesis of complementarity between organizational computing and skills in US firms. These scholars posit that the adoption of ICT is more effective in organizations with more skilled people and with decentralised workplace organization. It is the cluster of complementary inventions then that drives the productivity gains rather than the single components. Since there are different adjustment costs and adjustment timing across the complements, the effects on productivity are likely to occur only in the long run (see Brynjolfsson and Hitt, 2000). The adjustment time is firm-specific and therefore in the short run we should expect cross-sectional differences across firms. Arvanitis (2005) summarizes the empirical literature on different variants of the complementarity relationships between ICT, organizational change, and human capital in different countries. Most studies reviewed by Arvanitis show that ICT, human capital and a new workplace organization alone produce distinctive positive and significant effects on labour productivity. However, the evidence on complementarity is less clear and widespread. In the US and Australia various works have found evidence consistent with the hypotheses of complementarity between ICT and organizational change as well as between ICT and human capital (Bresnahan et al., 2002; Gretton et al., 2002), while in European countries like Germany, France and Switzerland the empirical evidence does not support the SBTC and the SBOC hypotheses together (Bertschek and Kaiser, 2004; Hempell, 2003; Caroli and Van Reenen, 2001).

Complementarity in small and large firms

It is reasonable to expect that large firms have a greater demand for all the complements compared with smaller firms; and therefore they should benefit from the use of ICT to a larger extent than smaller firms. In large firms there is a larger amount of information to be processed and a larger number of documents, tasks and people have to be coordinated. Several large organizations in the 1990s have introduced new forms of coordination, information sharing and decision-making and have invested in ICT. In line with the expected importance of large firms, existing empirical studies focus mainly on large firms (Bresnahan *et al*., 2002) or rely on samples where large firms are over-weighted (Caroli and Van Reenen, 2002) or pooled together with smaller firms (Bertschek and Kaiser, 2004). The potential differences between large firms and SMEs in the patterns of complementarity then remain largely unexplored.

This gap in the literature appears partly due to the fact that data on complementarity among skills, ICT investments and organizational change in smaller firms are difficult to obtain. But we believe that looking at the differences between large and small firms is important. The use of ICT in small and medium sized firms has increased over time as a consequence of declining quality-adjusted prices. There are reasons to believe then that the complementarity with organizational change and skill has set in motion a process of organizational adaptation that it is worthy to study. This could be especially the case of countries, like Italy, where small and medium sized firms account for a very important share of the economy. In this context it is interesting to see the productivity gains of those manufacturing firms which try to introduce both organizational and technical innovations.

Like large firms, small ICT-intensive firms must invest in skills to make their technological investments effective. Moreover, ICT increases the opportunities for communication and information sharing. This spurs a greater codification of procedural knowledge (procedural changes), which in turn calls for more skills. Skilled workers are important for planning and implementing new and more formalised procedures. In small firms investments in ICT and skills may be induced by business relations with large firms, which increasingly rely on electronic transaction systems such as customer relationship management and supply chain management. Obviously, compared with their larger counterparts, small firms' investments in organizational changes are constrained by the limited scale and complexity of operations and by their greater flexibility. And, to some extent, this may result in a trade-off between organizational change and skills. For instance, in small firms relatively complex tasks (e.g., accounting and auditing) are carried out by one or few skilled workers who do not need formal routines to communicate with other people within the organization.

3. Methodology

We employ different approaches for testing the implications of the hypothesis of complementarity between ICT, firm's organizational change, and skills.

3.1. Adoption approach

There are two main econometric approaches that are usually used in the literature for testing the hypothesis of complementarity. The most popular one is the *adoption approach*. The simplest version of this approach relies on reduced-form estimation of the investments in one of the complements conditional upon the adoption of other complements, controlling for other observable characteristics of the adopter. The underlying idea is that some particular inputs that can vary easily in the short term can be predicted by other firm's fixed or quasi-fixed choice inputs. In this context, complementarity implies a positive correlation between the levels of adoption of the hypothesized complements. However, estimations of reduced-form equations have the risk to get a simultaneous equations type of bias due to the endogeneity of the choice variables.

To handle with the problem of endogeneity of regressors in reduced-form equations, Arora and Gambardella (1990) and Arora (1996) suggest a one-sided test for complementarity which utilizes the conditional correlations between the residuals of reduced-form regressions of hypothesized complements on observable exogenous variables. This test has also some limitations, however, since the non-negativity of the variance-covariance matrix of residuals could be the result of unobserved exogenous variables that affect the endogenous inputs in a correlated way for reasons different from complementarity. To overcome this problem Bagüés (2004) has developed a test of complementarity that is based on the intertemporal structure of residuals. This test appears to be robust to the existence of omitted variables that are not serially autocorrelated. But, like other dynamic panel techniques, this approach relies on the assumption of stability of the complementarity effect across time and is very demanding in terms of longitudinal data.[5]

In this paper we first look at the correlations between residuals obtained from adoption regressions where the dependent variables are proxies for ICT, human capital and organizational change respectively. Our explanatory variables are a series of dummies which account for geographical location, firm size and sector. A high degree of correlation would imply that empirical models that estimate the impact of one of these variables on productivity will lead to biased results due to omission of other correlated choice variables. [6]

Second, following Bresnahan et al. (2002) we estimate equations of the determinants of short-term ICT and human capital investments as functions of other quasi-fixed complements. To reduce the problem of endogeneity we used lagged values of explanatory variables. The rationale for the choice of ICT and human capital policies as dependent variables is that they both represent control variables that a firm can modify in the short run. For instance, a firm can change from one year to the other its hiring policy or investments in training. Instead, substantial changes in the share of skilled labour and work organization practices normally take a longer time. The shortness of our panel prevented us from using dynamic panel techniques.

3.2.Production function approach with pair-wise interactions

An alternative method for testing complementarity is the *production function approach*. The test of complementarity in this context is based on the t-test of the pair-wise interactions between the potential complements (e.g., Bresnahan *et al*., 2002; Caroli and Van Reenen, 2001). The limitations of this method are apparent when the number of choice variables is greater than two (Lokshin *et al*., 2004). Estimates of pair-wise interaction effects ignore more complex linkages among more than two complements. At the same time, as it was argued by Ichniowski *et al*. (1997), putting all the interaction terms for the complements inside the regression would lead to confused results due to collinearity among regressors.

We use the production function approach for testing complementarity in the following way. We start from the standard estimation model, which is used in various earlier works (Bresnahan *et al*, 2002; Caroli and van Reenen, 2001):

$$\log(S_{it} - M_{it}) = f(L_{it}, K_{it}, Q_{cit}; controls), \qquad (1)$$

where S stands for sales, M is the materials bill (the dependent variable then is the log of the value added), L measures labour expenses, K is a measure of capital, and Q_{cit} is a measure of firm i's choice of one of the hypothesized group of complements in year t. The potential complements that we want to consider are the accumulated ICT stock, human capital and organizational change. Pair-wise interactions between potential complements or choice variables are also included among the regressors. We also add sector and geographical area dummies as controls. To deal with the problem of endogeneity we used lagged values of the explanatory variables except for non-ICT capital and labour cost. This has been done because we expect that changes in physical inputs produce short term effects on value added while changes in human capital, ICT and organizational structure are likely to produce less obvious short term productivity effects.

We also estimate a more complex model which includes the three-variable interaction term. The aim of this analysis is to see whether the productivity gains from the choice of a given pair of activities change with the adoption of a third activity. This provides a test of the *organizational complementarity* hypothesis discussed before.

We intend to see whether there are differences in the pattern of interaction between activities or co-inventions across different types of firms. For this purpose we compare the coefficients from regressions estimated on different sub-samples, which were defined according to firm size and sector.

In order to see whether changes in investments in the three activities or co-inventions affect changes in productivity in a complementary way we also estimate a version of the productivity equation in differenced form. This specification allowed us to deal with possible time-invariant unobserved heterogeneity across firms. For the purpose of this analysis, the estimation model (1) has been specified with the key variables taken in differences.

Finally, to account for potential sample selection of the decision variables we opted for a treatment effect estimator. If firms who have non zero investments in ICT would have attained the same level of productivity regardless of ICT investments then we have a problem of selfselection and ordinary least squares estimates in the productivity equation are biased (estimates tend to overestimate the effect of ICT on productivity). The treatment effect model accounts for the endogeneity of ICT (or other regressors like organizational change) by relying on Heckman's two step estimator or a full ML estimator (Greene, 1997).[7] In the first step a selection equation is estimated by regressing a dummy variable which takes value 1 if the treatment is positive on a vector of variables that affect the decision to invest in ICT. In the second step the regression equation (equation 1) is estimated with a term that controls for the effect of exogenous variables that explain ICT.

3.3. Production function approach with clusters of complements

Recent works on complementarity rely on multiple inequality restrictions (Wolak, 1989; Lokshin *et al*., 2004). These studies approach the problem of collinearity by identifying different clusters of patterns of adoption practices and compare the productivity outcomes of alternative clusters (Ichniowski *et al*., 1997).

Following these studies, we test the hypothesis of complementarity by relying on the theory of supermodularity of objective function which asserts the necessary conditions for two or more activities to be complements (Milgrom and Roberts, 1990). According to this theory two activities y_i and y_j are complements in the objective function f if the following inequality holds for all possible values of the other arguments of f (Athey and Stern, 1998):

$$f(y_i^H, y_j^H, \cdot) - f(y_i^L, y_j^H, \cdot) \geq f(y_i^H, y_j^L, \cdot) - f(y_i^L, y_j^L, \cdot), \qquad (2)$$

where H and L stand for high and low adoption intensity, respectively, and f is a measure of performance. Condition (2) posits that the marginal productivity of each activity increases with the adoption of the other[8].

To test the complementarity hypothesis according to the inequality restriction (2) we have used the mean values of ICT stock and human capital as thresholds for coding two dummy variables which take value "1" to indicate a relatively high level (above the mean) of the initial variable. Our measure of organizational change is a binary variable in the dataset and indicates whether organizational change has occurred during the past three years[9].

We use this methodology to test for pair-wise complementarity and complementarity among the three activities altogether.

For the test of pair-wise complementarity, we have generated three sets of clusters each corresponding to a combination of two dummy variables: [ICT – organizational change], [ICT – human capital], and [organizational change – human capital]. For each pair of dummies there are four possible clusters: (1,1), (1,0), (0,1), and (0,0).

We estimated three specifications of the production function, one for each clustering system with dummies for clusters as regressors. The coefficients of the dummy variables measure the gain from a given adoption strategy (e.g., ICT=1 and human capital=0) relative to non-adoption (ICT=0 and human capital=0).

These specifications of the production function estimation allow us to test the complementarity hypothesis based on the definition of complementarity described by the inequality in (2). This amounts to perform a Wald test on the following equality constraint

$$Coef.(s_{11}^{h}) = Coef.(s_{10}^{h}) + Coef.(s_{01}^{h}), \tag{3}$$

where s_{ij}^{h} is the dummy variable for clustering system h corresponding to the 'state' whereby the choice of the first activity (e.g., ICT) is equal to i and the choice of the second activity (e.g., human capital) is equal to j, $h \in \{1,2,3\}$ and $i, j \in \{0,1\}$ [10]. Values of the F-statistics above the threshold level reject the hypothesis of equality. When this is the case, the relative gain in productivity of firms with high adoption intensity of both inventions is larger than the sum of the gains from the adoption of each invention separately. This result would provide evidence in favour of the complementarity hypothesis.

Finally, we have created a clustering system containing eight clusters which characterize all possible states of adoption intensity of the three innovative activities simultaneously [ICT –

organizational change – human capital]. These clusters identify distinct groups of firms - from the most ‘traditional’ one (no adoption of ICT, no organizational innovations and low levels of human capital) to the most ‘innovative’ (the ‘modern’ firm), which takes advantage of modular production systems.

As we are interested in complementarity operationalized as strict supermodularity we checked whether the following three inequalities hold simultaneously:

$$\begin{aligned} &Coef.(v_{111}) > Coef.(v_{110}) + Coef.(v_{001}) \\ &Coef.(v_{111}) > Coef.(v_{101}) + Coef.(v_{010}) \\ &Coef.(v_{111}) > Coef.(v_{011}) + Coef.(v_{100}) \end{aligned} \qquad (4)$$

where v_{ijk} is the dummy variable corresponding to the state whereby the adoption intensity of ICT is equal to i, the adoption intensity of human capital is equal to j, and the adoption intensity of organizational change is equal to k, $i, j, k \in \{0,1\}$. When the three-variable complementarity inequalities above hold simultaneously the marginal productivity of each invention is higher if the other two inventions are both adopted simultaneously.

Notice that by adopting this methodology we lose a lot of information on variation because continuous variables are transformed into dummies. As a consequence, the precision of estimates may decrease compared with alternative approaches based on continuous regressors. To compensate for the drop in the amount of information in our estimations we use a large set of sector controls. However, this test for complementarity has its own advantages: it avoids the problems of multicollinearity and it is less restrictive in terms of imposing linear effects across the states of adoption.

4. Data and Variables Definition

4.1. Data

Our empirical analysis is based on data from a survey conducted by a leading Italian bank, *Mediocredito Centrale* (now *Capitalia*), in two waves – 1995-1997 and 1998-2000. Each survey includes data on a sample of Italian manufacturing firms, with at least 10 employees, belonging to different sectors, geographical areas and size classes.

The dataset provides three types of data for over 4,000 firms: a) balance sheet data for the period from 1989 to 2000; b) survey data on quantitative company characteristics (e.g., employment and investment) and qualitative variables such as the firm's group membership, its core sectors, innovation activity, and organizational change, for the periods 1995-1997 (t_1) and 1998-2000 (t_2). Several variables are observed only once every 3 years while others are available on an annual basis. The database is a statistically significant sample of the Italian manufacturing sector and was obtained by a stratified random selection process[11].

Our analysis draws on a panel of manufacturing firms, which participated in both waves of the survey. The sub-sample of 540 firms has been selected from a larger sample of 1302 firms in the panel.[12] Table 1 describes the composition of this sub-sample according to size, Pavitt (1984) sectoral classification and geographical area in 2000.

Over 61% of the sample firms are small (10 - 50 employees). Only 4% of firms operate in high tech sectors, while most firms belong to traditional and specialised suppliers sectors (about 39% and 31% respectively). [13]

Table 1. Sample composition

Size	Small (10-50 employees) 61.11%	Medium (51-250 employees) 29.44 %	Large (>250 employees) 9.44%	
Pavitt sector classification	Traditional sectors 38.52%	Scale-intensive production 26.48%	Specialized suppliers 30.74%	High-tech sectors 4.26%
Geographical area	North-East 43.52%	North-West 31.11%	Centre 15.74%	South 9.63%

N = 540

4.2. Variables Definition

From the dataset described above we extracted several variables that were used in econometric estimations as proxies for ICT stock and investment, human capital and organizational change. With the exception of capital and labour inputs, we always used the 1995-1997 values of the explanatory variables, and the 1998-2000 values of the dependent variables.

The definitions of the main variables are reported in Table 2.

Table 2. Description of variables

Variable	Description
ICT	
ICT inv	Total investments in ICT over 3 years before the survey
ICT stock 2000	Calculated from ICT investments by using a an extrapolation of Gordon's (1990) deflator for computers
HW inv	Hardware investment over 3 years before the survey
SW inv	Software investment over 3 years before the survey
TEL inv	Telecommunication investment over 3 years before the survey
Skills	
HIGHSKILL	Share of employees with a university degree in the 3rd year of the period covered by the survey
MIDSKILL	Share of employees with a upper secondary education in the 3rd year of the period covered by the survey
UNSKILLED	Share of employees with lower secondary education or less in the 3rd year of the period covered by the survey
HIGHMIDSKILL	Share of employees with either university degree diploma or high school education in the 3rd year of the period covered by survey
COURSES total	Number of employees participating in off-the-job training courses supplied by public or private educational centres during 3 years
QUALIF total	Number of hired employees with a university degree during 3 years
COURSES	Ratio of COURSES total to the average number of employees
QUALIF	Ratio of QUALIF total to the average number of employees
HK	QUALIF + COURSES
BLUE COLLARS	Share of blue collars in total number of employees, calculated from averages for 3 years
Organizational change	
ORG1	A dummy variable that takes the value one in the presence of organizational innovations induced by product innovations, and zero otherwise
ORG2	A dummy variable that takes value one in the presence of organizational innovations induced by process innovations, and zero otherwise
ORG	A dummy variable that takes value one in the presence of organizational innovations induced by process or product innovations, and zero otherwise
Other variables	
EMPLOY	Average number of employees during 3 years
VA	The value added at the last year of the survey period taken from the balance sheet of a firm
Fixed capital	Book value of physical capital stock (property, plants and equipment) at the end of each wave deflated by the GDP at the estimated age of the capital stock. The age is calculated as the average for the last 3-years of ratios of accumulated depreciation (amortization stock) to current depreciation, assuming a constant depreciation rate.
Labour expenses	The labour expenses at the last year of the survey period taken from firm's balance sheet

ICT stock and investments

As concerns the ICTs, we know the total ICT investments of the firm for the 3-year period covered by each survey. Our data make also possible to distinguish the share of ICT investments in computer hardware, software and telecommunications equipment.

By using this information we calculated non-ICT investment, ICT and non-ICT stocks. Since the survey provides the total ICT investment for 3 years, to obtain ICT stocks we deflated the value of ICT investments by using an extrapolation of Gordon's (1990) deflator for computers with price change α = 19.3 per cent per year (see Bresnahan *et al*., 2002).

The main problem with this measure is that it relies on a backward interpolation of past ICT investment flows.

We also constructed a variable which approximates the value of the non-ICT stock of the firm. Drawing on the methodology discussed by Hall (1990) we first estimated the age of the capital stock by calculating the 3-year average value of the ratio of net firm's assets to the annual amortization. The estimated value of the capital stock was deflated by the implicit price deflator of GDP at the calculated average age (base year=1995), and then to get a proxy of the non-ICT stock the value of the hardware and telecommunication share of ICT stock was subtracted from the total capital stock.

Workforce and skills

To measure the level of skills in the firms' workforce we selected three sets of variables. First, we considered the composition of the workforce by level of education: university education (HIGHSKILLED); upper secondary school education (MIDSKILLED); and low school education or less (UNSKILLED).

Second, we rely on the composition of the workforce by occupation, namely, we define the shares of production workers or blue collars (BLUE COLLARS) in the total number of a firm's employees.[14]

For estimation of the production function in differenced form we need a proxy of human capital change during the first period. The shortness of the panel does not allow us to proxy this flow by taking the difference between the values of human capital stock. Therefore, from our dataset we have extracted the following variables to proxy for human capital investment: (i) the ratio of hired employees with university education to total employees (QUALIF); and (ii) the share of employees participating in off-the-job training courses supplied by public or private educational centres (COURSES). The human capital variable (HK) has been obtained by summing QUALIF and COURSES. A limitation of our proxies is that they do not account for reductions in human capital generated by outflows of skilled employees.

Corporate restructuring and organizational change

We draw on the following two proxies for organizational change:

- a dummy for organizational change induced by firm's product innovations (ORG1);
- a dummy for organizational change induced by process innovations (ORG2).

We have also generated a variable that aggregates organizational changes induced by either product or process innovations - ORG.

Unfortunately, the dataset does not provide more detailed information about the nature of organizational changes, such as the adoption of new work practices like de-layering, teamwork, and job rotation[15]. The lack of detailed information on firm-level organizational change has also led earlier studies to resort to proxies for the occurrence of organisational change such as dummies (Caroli *et al*., 2001; Piva *et al*., 2005) and the level of product turnover as a measure of "creative destruction" within the organisation (Thesmar and Thoenig, 2000).

The use of ORG1 and ORG2 variables by construction should be strictly related with product and process innovations and this may bias our analysis. This is especially the case of organizational change associated with process innovations, which may include the adoption of ICT. We analyzed the correlation between these measures of organizational change and product or process innovation in the same period and found that in fact they are not strongly correlated. 10% of the sample firms that have tried organizational innovations induced by process innovations in 1995-1997 have not introduced any process innovation in the same period. On the other hand, while 74% of firms have experienced process innovations only 35% of them have tried organizational change induced by process innovations in the same period. Similar results were obtained when looking at organizational changes induced by product innovations. This suggests that our measures of organizational change tend to be correlated with technical change in the long run, not in the short run. This reduces the problem of contemporaneous correlation with ICT, even if does not remove other drawbacks of this variable.

4.3. Descriptive Statistics

Table 3 reports the descriptive statistics of the main variables used in the econometric analysis, while Table 4 describes the same variables by firm size.

The sample firms invested an average amount of 168 thousand Euros in ICT in 1998-2000, which represents a 5% increase compared to 1995-1997 (Table 3). Hardware and software accounted for the largest share of ICT investments - respectively 47.6% and 44.5% in 1998-2000. From t_1 to t_2 the shares of software and telecommunication investments have increased at the expense of hardware.

With respect to the skill composition of the workforce, in 1995-1997 on average 59% of the employees had a lower secondary school diploma (UNSKILLED), 37 % an upper secondary level of education and only 4% a university degree. In line with the level of education, 68% of employees on average are blue collars. In addition, in t_1 the human capital investment variables show that the share of new graduates on total employment was 1.2% and the share of workers participating in training courses is 3.8%. These two variables increased slightly in t_2. Finally, in t_1 17 % of companies have experimented organizational changes induced by product innovation and 29% by process innovation. 34 % of the firms have tried at least one of the two types of organizational change (ORG1 and ORG2), while 12% have introduced both types. In t_2 organizational changes induced by both types of innovation have become more frequent.

Table 3. Descriptive statistics for the main variables

	N	Mean	St. Dev.	Min	Max	N	Δ, mean difference in absolute values
	t_2 (1998-2000)					*t_2-t_1*	
Value added (last year of the 3-year period) (VA) (*)	540	6015.88	19560.63	57.61	336798	525	1252.67
Investments in ICT (total for 3 years) (ICTinv) (*)	540	168.15	559.21	0..918	9361.47	540	8.49
Share of hardware in ICT investment (HW)	540	0.476	0.218	0	1	540	-0.048
Share of software in ICT investment (SW)	540	0.445	0.215	0	1	540	0.018
Share of telecommunication in ICT investment (TEL)	540	0.079	0.117	0	0.8	540	0.029
University graduated hired during 3 years per employee (QUALIF)	501	0.013	0.035	0	0.55	344	0.002
Share of participants in training courses (COURSES)	528	0.041	0.084	0	1	522	0.004
	t_2 (1998-2000)					*t_2-t_1*	
Labour Cost (last year of the 3-year period) (*)	540	3094.72	8175.04	70.80	114139	525	201.32
Non-ICT stock (last year of the 3-year period) (*) (**)	540	5954.83	47404.58	7.35	1085071		
	t_1 (1995-1997)					*t_2-t_1*	
Number of employees (EMPLOY)	540	102.99	264.10	10.33	3642.67	537	5.44
Investments in ICT (total for 3 years) (ICTinv) (*)	540	160.66	551.15	0.998	9084.48	540	8.49
Workforce and skills							
Share of employees with lower secondary school diploma (UNSKILLED)	540	0.59	0.25	0	1	452	0.062
Share of employees with upper secondary school diploma (MIDSKILLED)	540	0.37	0.23	0	1	462	-0.047
Share of employees with university degree (HIGHSKILLED)	540	0.04	0.06	0	0.41	461	-0.001
University graduated hired during 3 years per employee (QUALIF)	372	0.012	0.034	0	0.32	344	0.002
Share of participants in training courses (COURSES)	534	0.038	0.112	0	1	522	0.004
Human capital investment (HK)	371	0.047	0.108	0	1.05	336	0.015
Share of production workers (BLUE COLLARS)	540	0.68	0.16	0	0.97	534	-0.001
Organizational change							
Organizational changes induced by product innovations (ORG1)	540	0.17	0.38	0	1	537	0.039
Organizational changes induced by process innovations (ORG2)	540	0.29	0.45	0	1	537	0.052
Organizational changes induced either by process or product innovations (ORG)	540	0.34	0.47	0	1	537	0.069

Notes: (*) Values in thousands of Euros.
(**) Defined only for t_2.

Table 4 illustrates the same set of variables across large, medium and small firms. As expected, the level of investments in ICT (the total amount and the amount per employee) increases with firm size. The share of hardware is relatively larger in small firms, while large firms have a higher proportion of telecommunication investments. We can also observe that large firms invest more intensely in human capital as compared with other companies. Table 4 shows that on average workers employed by large firms have a higher level of education. The share of employees with a tertiary education is 6% in large firms and 4% in SMEs. Moreover, large firms invest more in upskilling their human capital, as highlighted by the larger share of new graduated employees and of employees participating to training courses.

Organizational change is also more frequent in larger firms. 29% of large firms experienced organizational change induced by product innovation against 23% of medium firms and 12% of small firms. Organizational change induced by process innovation is more frequent in all size classes (41% in large firms, 35% in medium and 24% in small firms). These data confirm that organizational change is less marked in small firms, where organizational settings are more informal or less codified.

Table 4. Mean values of ICT, skills and organizational change variables by firm size

	Small			Medium			Large		
	N	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**
				t_2 (1998-2000)					
VA (*)	330	1444.09	(1064.79)	159	5421.07	(3411.337)	51	37452.44	(54159.91)
ICT investment (*)	330	39.92	(54.23)	159	162.35	(189.07)	51	1026.61	(1542.21)
HW	330	0.49	(0.22)	159	0.45	(0.21)	51	0.47	(0.23)
SW	330	0.44	(0.22)	159	0.47	(0.21)	51	0.42	(0.23)
TEL	330	0.08	(0.13)	159	0.08	(0.10)	51	0.11	(0.11)
COURSES	329	0.039	(0.085)	151	0.040	(0.078)	48	0.058	(0.094)
QUALIF	322	0.012	(0.040)	141	0.013	(0.026)	38	0.016	(0.021)
				t_2 (1998-2000)					
Labour Cost (*)	330	739.04	(367.28)	159	3066.85	(1917.67)	51	18424.26	(20775.26)
Non-ICT stock (*)	330	1121.57	(1319.54)	159	4555.55	(4819.73)	51	41591.37	(150612.5)
				t_1 (1995-1997)					
EMPLOY	330	27.65	(9.57)	159	103.35	(47.20)	51	589.44	(682.23)
ICT investment (*)	330	46.93	(77.48)	159	151.19	(226.39)	51	926.03	(1545.94)
Workforce and skills									
HIGHSKILLED	330	0.04	(0.07)	159	0.04	(0.05)	51	0.06	(0.07)
MIDSKILLED	330	0.38	(0.24)	159	0.33	(0.22)	51	0.39	(0.18)
UNSKILLED	330	0.58	(0.25)	159	0.63	(0.24)	51	0.54	(0.22)
COURSES	326	0.036	(0.116)	159	0.030	(0.081)	49	0.068	(0.148)
QUALIF	208	0.010	(0.037)	124	0.011	(0.024)	40	0.019	(0.030)
HK	207	0.044	(0.117)	124	0.038	(0.055)	40	0.089	(0.161)
BLUE COLLARS	330	0.66	(0.16)	159	0.73	(0.13)	51	0.69	(0.17)
Organizational change									
ORG1	330	0.12	(0.33)	159	0.23	(0.43)	51	0.29	(0.46)
ORG2	330	0.24	(0.43)	159	0.35	(0.48)	51	0.41	(0.50)
ORG	330	0.28	(0.45)	159	0.43	(0.50)	51	0.43	(0.50)

Note: (*) Values in thousands of Euros

5. Results

5.1. Conditional correlations

Table 5 reports the Pearson's correlation between residuals of the reduced-form regressions of the potential complements (ICT, human capital and organizational change) against a set of controls. A common set of dummies for geographical location, firm size, sector, and time period have been used across all regressions. Note that positive correlations between residuals provide evidence consistent with the hypothesis of pair-wise complementarity.

The correlations between the residuals of ICT investments and those of other complements have the expected signs. ICT investments are positively associated with the share of workers with an upper secondary school diploma and/or a university degree. The share of blue collars is negatively associated with the ICT investments. The correlation between ICT investments and various measures of investments in human capital are also positive and significant.

The measures of organizational change (ORG1, ORG) are positively correlated with ICT investments. Organizational change appears to be negatively correlated with the level of skills. On the contrary, it is positively and significantly correlated with the measures of human capital investment.

The correlations between residuals of non-ICT investment intensity and skills (education and occupation variables) have significantly lower coefficients than those of ICT investment. Instead, non-ICT investments have higher correlation with organizational change related to process innovations.[16] This result is in line with earlier works showing that the relation between skills, organizational change and technical change is specific to ICT rather than being a general pattern of technical change (see for example, Bresnahan *et al*. 2002).

It is worth to note that this test does not control for the possibility of unobserved exogenous factors unrelated to complementarity or a common measurement error that affect the hypothesized variables in a correlated way.

Table 5. Correlations between ICT, skills and organizational change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) ICT inv/EMPLOY	1												
(2) Non ICT/EMPLOY	0.265***	1											
(3) UNSKILLED	-0.198***	-0.082**	1										
(4) MIDSKILLED	0.162***	0.074**	-0.977***	1									
(5) HIGHSKILLED	0.216***	0.070*	-0.373***	0.172***	1								
(6) HIGHMIDSKILL	0.198***	0.084**	-1.000***	0.978***	0.375***	1							
(7) BLUE COLLARS	-0.171***	0.038	0.398***	-0.326***	-0.438***	-0.400***	1						
(8) COURSES	0.158***	0.042*	-0.087**	-0.002	0.420***	0.088**	-0.132***	1					
(9) QUALIF	0.111***	0.067	-0.076**	0.035	0.205***	0.076**	-0.126***	0.244***	1				
(10) HK	0.152***	0.072*	-0.094**	0.028	0.320***	0.095**	-0.150***	0.553***	0.942***	1			
(11) ORG1	0.117***	0.052	0.042	-0.057	0.054	-0.042	-0.037	0.149**	0.085***	0.124***	1		
(12) ORG2	0.041	0.149***	0.069*	-0.067*	-0.031	-0.069	0.011	0.047*	0.063	0.071*	0.392***	1	
(13) ORG	0.058	0.132***	0.049	-0.053	0.003	-0.049	-0.023	0.064*	0.081**	0.084**	0.607***	0.884***	1

Note: (*) Correlations were calculated for the pooled data from t1 and t2.

5.2. Determinants of short term ICT and human capital investments

Tables 6 and 7 give the results of our second test based on the adoption approach, performed by estimating the equations of the determinants of short-term ICT and human capital investments as functions of other quasi-fixed complements.

Table 6 shows the OLS estimates of the marginal effects of skills, investments in human capital, and organizational changes observed in the first period on the ICT investments in the following period. We control for firm sector and geographical location and within-process variety (proxied by the share of blue collars). The results of the OLS regressions in columns (1) to (6) show that organizational changes driven by product innovations and investment in human capital by hiring qualified labour are good predictors of ICT investments. The collinearity among regressors reduces the size and precision of some marginal effects. For instance, the inclusion of the share of blue collars absorbs the effect of the share of skilled workers (column (2) and (3)).

To study the determinants of ICT investments in different size classes, we run separate regressions for small and medium firms. We do not estimate the equation for the sub-sample of large firms because of the small number of observations. The estimates reported in columns (8) and (9) clearly indicate that the effect of investment in human capital (QUALIF) is large and significant for medium firms whereas the effect of organizational change (ORG1) is large and significant only for small firms. This result is interesting as it signals that we should expect different patterns of interaction across firms of different size, and thus the inferences based on the analysis of pooled samples could be misleading.

Finally, our results show that non-ICT investments are positively and significantly correlated with training courses and not with hiring of qualified labour as in the case of ICTs. At the same time, non-ICT investments are positively even if not significantly correlated with the share of blue-collar workers. This observation provides support to the hypothesis that the skill-biased technical change is specific to ICT rather than technical change in general.

Table 6. OLS estimates of determinants of ICT and Non-ICT investments in 2000.

	LogICTinv (1)	LogICTinv (2)	LogICTinv (3)	LogICTinv (4)	LogICTinv (5)	LogICTinv (6)	LogICTinv (7) Heckman model (*)	LogICTinv (8) Small firms	LogICTinv (9) Medium firms	Log nonICTinv (10)
Constant	1.176***	1.190***	-0.328	1.144***	1.175***	1.099**	1.720***	1.586**	2.155	1.799***
	(0.373)	(0.426)	(0.310)	(0.434)	(0.369)	(0.435)	(0.419)	(0.780)	(1.580)	(0.689)
QUALIF 1997				3.776***		3.107**	3.097**	1.266	7.157*	3.999
				(1.332)		(1.332)	(1.258)	(1.621)	(3.772)	(2.799)
COURSES 1997				0.328		0.238	0.050	0.591	2.670	1.227**
				(0.836)		(0.852)	(0.689)	(1.447)	(2.035)	(0.523)
ORG1 1997					0.307*	0.274	0.279*	0.593**	-0.090	0.280
					(0.171)	(0.173)	(0.159)	(0.246)	(0.276)	(0.253)
ORG2 1997					0.030	0.020	0.023	-0.064	0.055	0.126
					(0.146)	(0.150)	(0.138)	(0.222)	(0.236)	(0.222)
HIGHMIDSKILL 1997		-0.018	0.373	-0.027		0.043	-0.085	0.129	-0.089	0.555
		(0.234)	(0.236)	(0.234)		(0.236)	(0.217)	(0.304)	(0.387)	(0.341)
BLUE COLLARS 1997	-2.083***	-2.094***		-1.954***	-2.059***	-1.918***	-1.794***	-1.999***	-2.181**	0.826
	(0.424)	(0.440)		(0.440)	(0.418)	(0.436)	(0.424)	(0.506)	(0.966)	(0.740)
LogEMPLOY 1997	1.073***	1.074***	1.032***	1.054***	1.052***	1.039***	1.037***	0.930***	0.848***	0.946***
	(0.064)	(0.064)	(0.063)	(0.065)	(0.063)	(0.065)	(0.063)	(0.214)	(0.241)	(0.078)
Controls:										
Pavitt sectors	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Geogr. Area	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.523	0.523	0.492	0.529	0.530	0.534		0.177	0.230	0.349
N	329	329	329	329	329	329	549	174	117	329

* p<0.10, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Note: (*) Test of sample selection based on positive ICT investment in 1997 and 2000, instruments: 2-digit Ateco code, macro-region (Nielsen), time of firm foundation (by decade). Wald test: chi2 = 12.01, Prob > chi2 = 0.0005.

Table 7 shows the results of negative binomial estimations of the determinants of human capital investments. Our findings suggest that ICT investments, skills and organizational change induced by process innovations are good predictors of this type of firm strategy. We estimated two separate equations for QUALIF total and COURSES total as dependent variables. ICT investments are positively associated to both human capital policies. The share of skilled labour affects positively the human capital investments especially when QUALIF is used as dependent variable while the share of blue collars in the total workforce has a negative, although non significant effect. When ICT investments are included among the regressors the share of skilled labour becomes not significant in estimation of COURSES (equations 5 and 6). Organizational change induced by process innovation positively and significantly affects the investments in training and the upskilling of the labour force. However, when ICT investments are included in the regression, the coefficient for ORG2 becomes non significant in the estimation of QUALIF. Organizational change induced by product innovation is never related to human capital policies.

Table 7. Negative binomial regression results for human capital investment in 2000

	QUALIF total 2000 (1)	QUALIF total 2000 (2)	QUALIF total 2000 (3)	COURSES total 2000 (4)	COURSES total 2000 (5)	COURSES total 2000 (6)
Constant	-5.031*** (0.669)	-4.931*** (0.636)	-5.077*** (0.653)	-2.377*** (0.641)	-2.634*** (0.672)	-2.851*** (0.630)
Log (ICTinv / EMPLOY) 1997		0.426*** (0.105)	0.409*** (0.100)		0.353*** (0.073)	0.340*** (0.072)
ORG1 1997	-0.055 (0.275)		0.079 (0.269)	-0.149 (0.224)		-0.218 (0.215)
ORG2 1997	0.504** (0.254)		0.357 (0.229)	0.727*** (0.206)		0.635*** (0.192)
HIGHMIDSKILL 1997	1.234*** (0.410)	0.758** (0.363)	0.915** (0.378)	0.718** (0.351)	0.273 (0.342)	0.447 (0.331)
BLUE COLLARS 1997	-1.197* (0.708)	-0.828 (0.654)	-0.702 (0.677)	-1.106 (0.719)	-0.344 (0.751)	-0.215 (0.719)
LogEMPLOY 1997	1.068*** (0.109)	1.088*** (0.087)	1.055*** (0.097)	1.148*** (0.086)	1.173*** (0.215)	1.140*** (0.081)
Alpha (*)	2.569 (0.388)	2.307 (0.332)	2.236 (0.329)	4.174 (0.373)	4.127 (0.370)	4.022 (0.363)
Controls: 1997						
Pavitt sectors	YES	YES	YES	YES	YES	YES
Geogr. Area	YES	YES	YES	YES	YES	YES
Pseudo R2	0.120	0.131	0.134	0.062	0.064	0.067
N	494	494	494	494	494	494

* p<0.10, **p<0.05, ***p<0.01. Robust standard errors in parenthesis.

Table 8 reports the results of the negative binomial estimations regression of the human capital policies for the sub-samples of small and medium firms. In these specifications small and medium firms appear to be quite similar. For both types of firms ICT investments are significant for skill upgrading, as posited by the SBTC hypothesis. Both in small and in medium firms organizational change induced by process innovation is more important for the decision of investing in training than in hiring. At the same time, the hiring polices are always associated with the previous occupational and educational mix of employees. In medium firms the share of skilled labour stimulates further hiring of skilled personnel, while in small firms the share of production workers has a negative effect on upskilling of labour force.

The estimation results discussed above could be driven by unobserved shocks that cause the change of innovation strategies in a correlated way. In theory there are several sources of heterogeneity that could bias our estimations such as demand efficiency advantages (skilled managers), firm size (larger firms may tend to demand more of all complements because of scale effects), managerial rents and free cash flow (managers of successful firms may want to invest more in IT and skills for reasons unrelated to complementarity), worker rents (workers may be willing to use computers for fad). Our estimations account for some of these sources of heterogeneity, especially firm size. Moreover, our regressors are lagged to deal with transitory shocks (such as an exceptional increase of output demand or efficiency), which can affect both ICT demand and other covariates leading to spurious correlations. To deal with the issue of endogeneity we have also used lagged values of regressors as instruments. Instrumental variable estimates yield similar results as OLS (not shown) providing evidence consistent with the hypothesis of complementarity between ICT investments and other innovative activities.

Table 8. Negative binomial regression results for human capital investment in 2000, small and medium firms

	QUALIF total 2000	QUALIF total 2000	COURSES total 2000	COURSES total 2000
	(1) small	(2) medium	(3) small	(4) medium
Constant	-5.884***	-6.949***	-2.681**	-1.016
	(0.419)	(2.061)	(1.058)	(2.122)
Log (ICTinv / EMPLOY) 1997	0.419***	0.229***	0.330***	0.324**
	(0.138)	(0.143)	(0.090)	(0.148)
ORG1 1997	-0.522	0.310	-0.057	-0.498
	(0.551)	(0.372)	(0.292)	(0.360)
ORG2 1997	0.505*	0.109	0.593**	0.908***
	(0.285)	(0.351)	(0.251)	(0.305)
HIGHMIDSKILL 1997	0.562	1.472**	0.371	0.584
	(0.523)	(0.721)	(0.425)	(0.670)
BLUE COLLARS 1997	-1.493*	0.122	-0.099	-0.807
	(0.900)	(1.383)	(0.902)	(1.665)
LogEMPLOY 1997	1.545***	1.249***	1.045***	0.841***
	(0.394)	(0.337)	(0.300)	(0.291)
Alpha (*)	2.256	1.939	4.012	3.691
	(0.612)	(0.410)	(0.477)	(0.590)
Controls: 1997				
Pavitt sectors	YES	YES	YES	YES
Geogr. Area	YES	YES	YES	YES
Pseudo R2	0.105	0.079	0.037	0.021
N	321	135	321	135

* p<0.10, **p<0.05, ***p<0.01. Robust standard errors in parenthesis.

5.3. Productivity equations

This section analyzes complementarity in the context of the production function. It is worth to note that the production function approach aims at capturing differences across firms that use different combinations of complements. As mentioned before, differences in adaptation costs, information barriers, and timing will result in different short-term combinations of complements, which in turn will be transferred into different productivity levels.

5.3.1. Productivity equations with interaction terms

We start with the estimation of a simple productivity equation with the logarithm of the value added as dependent variable. Our regressors include the three complements and their interactions.

We control for the effect of traditional inputs (non-ITC capital and labour), sector and location of the firm.

The OLS estimates reported in Table 9 yield quite interesting results. Equation (1) suggests that there is no direct effect of skills on firms' productivity while the marginal effects of ICT and organizational change are both positive and significant. Although collinearity between ICT stock, skills and organizational change reduces the precision of marginal effects, the interaction term for ICT and human capital reported in column (2) is positive and strongly significant, as predicted by the complementarity theory. The interaction terms between organisational change and skills (column 3) and between organisational change and ICT (column 4) are also positive; however, they remain outside the conventional region of significance. When controlling for higher-order interaction effects among the three complements (column 6), all pair wise complementarity effects remain positive and become significant. Instead, the coefficient of the three-variable interaction term is negative and significant, in contrast with the *organizational complementarity* hypothesis.

Table 9. Production function estimates with interactions

	LogVA2000	LogVA2000	LogVA2000	LogVA2000	LogVA2000	LogVA2000	LogVA2000 Treatment effect model (*)
	(1)	(2)	(3)	(4)	(5)	(6)	(6)
Constant	0.751*** (0.094)	0.926*** (0.114)	0.774*** (0.095)	0.784*** (0.099)	0.951*** (0.118)	1.032*** (0.134)	1.016*** (0.148)
Log(NonICTstock 2000)	0.069*** (0.016)	0.071*** (0.016)	0.068*** (0.016)	0.068*** (0.016)	0.070*** (0.016)	0.069*** (0.016)	0.069*** (0.015)
Log(Labour costs 2000)	0.886*** (0.026)	0.887*** (0.026)	0.887*** (0.026)	0.887*** (0.026)	0.884*** (0.026)	0.885*** (0.025)	0.885*** (0.025)
Log(ICTstock1997)	0.027* (0.014)	-0.011 (0.022)	0.026* (0.014)	0.025 (0.016)	-0.013 (0.023)	-0.034 (0.027)	-0.035 (0.027)
ORG 1997	0.061** (0.025)		-0.003 (0.045)	0.015 (0.094)	-0.022 (0.095)	-0.272* (0.165)	-0.287* (0.164)
HIGHMIDSKILL 1997	0.051 (0.059)	-0.368** (0.180)	0.004 (0.074)		-0.364** (0.177)	-0.562** (0.237)	-0.587** (0.240)
LogICTstock1997 * HIGHMIDSKILL1997		0.091** (0.037)			0.087** (0.037)	0.130*** (0.040)	0.138*** (0.052)
HIGHMIDSKILL1997 * ORG1997			0.173 (0.111)		0.119 (0.114)	0.751** (0.334)	0.776** (0.337)
LogICTstock1997 *ORG1997				0.009 (0.019)	0.008 (0.019)	0.064* (0.036)	0.067* (0.036)
LogICTstock1997 * ORG1997 * HIGHMIDSKILL1997						-0.136* (0.070)	-0.141* (0.071)
Controls 1997							
Pavitt sector	YES	YES	YES	YES	YES	YES	YES
Geogr. Area	YES	YES	YES	YES	YES	YES	YES
R2	0.935	0.935	0.935	0.935	0.936	0.937	
N	540	540	540	540	540	540	829

* p<0.10, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Notes: (*) Treatment: ICT investment in 1997 and 2000, instruments: 2-digit Ateco code, macro-region (Nielsen), foundation time (by decade). Wald test: chi2 = 0.39, Prob > chi2 = 0.5326.
In other specifications in which *ORG* is substituted by *ORG1* or *ORG2*, all the coefficients are not significantly different from those shown above.

To account for unobserved firm-specific heterogeneity, we have also estimated a productivity equation in differenced form (Table 10). For this specification we employed ORG 1997 as a proxy for change in the firm's organizational structure, and HK1997 as a proxy for changes in the firm's stock of human capital. The results confirm the findings discussed before. The interactions between ICT and human capital investment and between organizational change and human capital investment, respectively, remain positive and strongly significant (equation 6). Similar to estimation in levels, the pair-wise interaction between ICT and organizational change has a small, insignificant effect.

The strong negative effect of the three-variable interaction term confirms the results of estimations in levels.

Table 10. Production function estimation with variables in differences and interaction terms

	logVA 97-00	logVA 97-00	logVA 97-00	LogVA 97-00	logVA 97-00	logVA 97-00	logVA 97-00 Heckman model (*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.136*** (0.050)	0.167*** (0.052)	0.150** (0.050)	0.139* (0.059)	0.164*** (0.061)	0.213*** (0.064)	0.211*** (0.079)
Log NonICTinv 2000 (**)	0.005 (0.007)	0.003 (0.007)	0.004 (0.007)	0.005 (0.007)	0.003 (0.007)	0.002 (0.007)	0.002 (0.007)
Log Labor costs97-00	0.781*** (0.075)	0.783*** (0.073)	0.781*** (0.075)	0.781*** (0.075)	0.788*** (0.073)	0.800*** (0.073)	0.800*** (0.071)
Log ICTinv 1997	-0.004 (0.009)	-0.011 (0.011)	-0.004 (0.009)	-0.005 (0.011)	-0.007 (0.011)	-0.020 (0.013)	-0.019 (0.013)
ORG 1997	-0.011 (0.025)		-0.033 (0.029)	0.028 (0.073)	-0.005 (0.072)	-0.068 (0.081)	-0.068 (0.079)
HK 1997	0.068 (0.245)	-0.652* (0.594)	-0.188 (0.149)		-0.684 (0.506)	-2.214*** (0.718)	-2.212*** (0.707)
Log ICTinv 1997 * HK1997		0.164 (0.160)			0.129 (0.131)	0.532*** (0.198)	0.532*** (0.194)
HK1997 * ORG1997			0.474 (0.359)		0.354 (0.224)	2.227*** (0.859)	2.228*** (0.837)
Log ICTinv 1997 * ORG1997				0.005 (0.018)	-0.006 (0.017)	0.012 (0.021)	0.012 (0.020)
Log ICTinv * ORG1997 * HK1997						-0.474* (0.252)	-0.474* (0.247)
Controls 1997							
Pavitt sector	YES	YES	YES	YES	YES	YES	YES
Area	YES	YES	YES	YES	YES	YES	YES
R2	0.327	0.335	0.335	0.327	0.340	0.348	
N	316	316	316	316	316	316	605

* p<0.10, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Notes: (*) Test of sample selection based on positive ICT investment in 1997 and 2000, instruments: 2-digit Ateco code, macro-region (Nielsen), foundation time (by decade). Wald test: chi2 = 0.00, Prob > chi2 = 0.9662.
(**)The logarithm of non-ICT investment is used as a proxy of change in the non-ICT stock due to the big number of missing values in non-ICT stock variable in t_1.
In other specifications in which HK is substituted by *QUALIF* or *COURSES* and *OC* is substituted by *ORG1* or *ORG2*, all the coefficients are not significantly different from those shown above.

In order to understand better how firm size affects the findings discussed above, we carried out production function estimations on sub-samples of firms belonging to different size classes. Table 11 summarizes the estimation results for the productivity equation (1) with the inclusion of all interaction terms.

The comparison of estimation results across the three sub-samples suggests that the results presented before are mainly driven by medium-sized firms. Medium-sized firms have stronger productivity gains from the interactions between couples of co-inventions than small firms, although the estimates of pair-wise interaction terms are significant only when the three-variable interaction term is entered in the production equation. In small firms only the interaction between skills and ICT yields positive, significant effects on productivity whether or not the three-variable interaction term is included among regressors. The small number of large firms in our sample does not allow to reach any robust conclusions about complementarity although the positive sign of the triple-wise interaction term suggests that large firms have greater opportunities to exploit the benefits of *organizational complementarity* as compared with smaller firms[17].

These results are consistent with the fact that in small firms there is limited scope for productivity gains associated with organizational changes. In medium sized firms, instead, the potential benefits of ICT probably require more substantial organizational changes such as de-layering and team production. However, the estimates reported in Table 11 clearly show that, especially in medium sized firms, the adoption of a third innovation activity yields negative effects on productivity. One possible explanation for this result which contradicts the hypothesis of organizational complementarity is related to the estimation methodology. As mentioned before, the complexity of interactions among regressors and multicollinearity may lead to confounding estimates. As will be discussed later, another explanation could be that small-to-medium firms have a limited ability to manage a complex set of co-inventions. Unfortunately, the limited number of observations does not allow to examine organizational complexity in large firms.

To illustrate the complexity of interactions between ICT, organizational change and skills we focus on medium firms. To this purpose we analyzed the derivatives of the LogVA to LogICT at different levels of skills (Figure 1) and the derivatives of LogVA to HIGHMIDSKILLS at different levels of LogICT (Figure 2) in firms with and without organizational change respectively. We than looked at the position of the confidence intervals of these derivatives with respect to zero Figure 1 clearly shows that on average firms with limited human capital do not experience productivity gains from ICT investments. The marginal productivity of ICT investments increases with the stock of human capital in firms which have not introduced any organizational change. On the contrary, in firms with organizational change the marginal productivity of ICT decreases with increasing levels of human capital. By the same token, the marginal productivity of human capital reported in Figure 2 increases with the level of ICT investments in firms which have not tried any organizational change and decreases in firms with organizational change.

Table 11. Production function estimates across size groups

	LogVA 2000	LogVA 2000	LogVA 2000	LogVA 2000	LogVA 2000	LogVA 2000
	Small		Medium		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.737** (0.307)	0.794** (0.319)	1.638*** (0.441)	1.904*** (0.450)	-0.628 (1.290)	-1.776 (2.156)
LogLaborExp 2000	0.933*** (0.059)	0.929*** (0.059)	0.733*** (0.057)	0.750*** (0.058)	1.016*** (0.131)	1.046*** (0.161)
LogNonICTstock 2000	0.056*** (0.018)	0.058*** (0.018)	0.133*** (0.024)	0.124*** (0.025)	0.021 (0.63)	0.027 (0.064)
LogICTstock 1997	-0.008 (0.034)	-0.019 (0.040)	-0.033 (0.053)	-0.096* (0.052)	0.107 (0.092)	0.229 (0.169)
HIGHMIDSKILL 1997	-0.503* (0.275)	-0.602* (0.337)	-0.320 (0.383)	-1.064** (0.429)	1.586 (0.951)	3.275 (2.020)
ORG 1997	0.124 (0.143)	-0.054 (0.238)	-0.021 (0.233)	-1.000*** (0.329)	-0.108 (0.411)	1.190 (1.310)
LogICTstock 1997 * ORG 1997	-0.036 (0.034)	0.012 (0.060)	0.006 (0.047)	0.200*** (0.064)	0.033 (0.064)	-0.154 (0.191)
LogICTstock 1997 * HIGHMIDSKILL 1997	0.113* (0.066)	0.140* (0.083)	0.101 (0.082)	0.244*** (0.084)	-0.237 (0.142)	-0.492 (0.306)
HIGHMIDSKILL 1997 * ORG 1997	0.179 (0.136)	0.610 (0.453)	-0.022 (0.208)	2.853*** (0.426)	0.288 (0.322)	-2.502 (2.231)
LogICTstock 1997 * HIGHMIDSKILL 1997 * ORG 1997		-0.111 (0.114)		-0.563*** (0.121)		0.391 (0.306)
Controls:						
Sector	YES	YES	YES	YES	YES	YES
Geographical area	YES	YES	YES	YES	YES	YES
R-sq.	0.748	0.748	0.806	0.824	0.947	0.950
N	330	330	159	159	51	51

* p<0.10, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

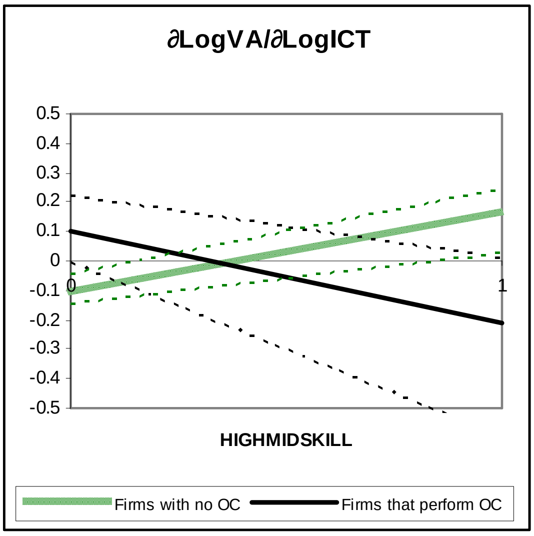

Figure 1. Marginal productivity of ICT for different levels of skills in medium firms.

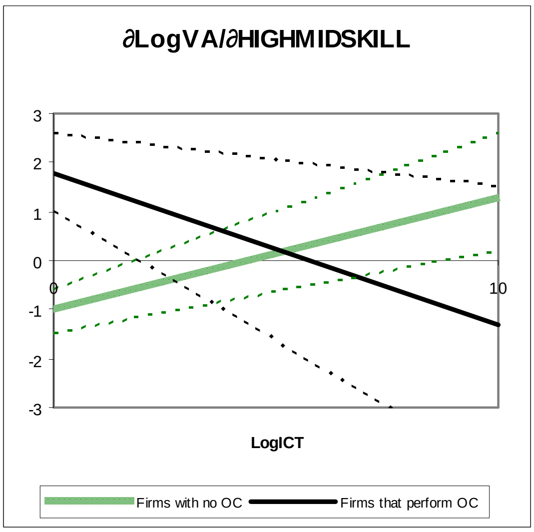

Figure 2. Marginal productivity of skills for different levels of ICT adoption in medium firms.

5.3.2. Productivity equations with clusters of complements

As noted in previous studies and discussed in the methodological section, the introduction of multiple interaction terms in the context of the production function can generate misleading results because of the collinearity among the hypothesized complements. Additional problems could arise from the assumption of linear complementarity effects across the states of adoption. To check for this source of biases and misspecifications we tried an alternative regression approach.

Following the methodology discussed in Section 3.3, we identified clusters of firms with different pairs and triples of innovation strategies. These clusters were obtained by using variables observed in t_1. Table 12 reports the distribution of firms by cluster for the total sample and for the sub-samples of small, medium and large firms. The Table shows that a large proportion of firms (about 25%) does not adopt intensively any of the three innovation strategies(V_{000})[18]. This proportion decreases with firm size - only about 15% of large companies do not adopt any of the three innovation strategies.

By contrast, only 6.3 % of all companies adopt simultaneously the three strategies and, as expected, a substantial proportion of large firms belongs to this cluster (15.69%).

About 42.41% of firms adopt only one strategy, while 25.56% of firms adopt simultaneously two strategies. Again, medium and large firms are more likely to adopt two strategies than small firms. In general, the joint adoption of ICT and human capital is clearly more frequent than that of OC and skills (compare V_{110} with V_{011}).

These descriptive statistics point out that simultaneous innovations are not very frequent even in large firms. For smaller firms in particular this result is partly due to the cost and complexity of a simultaneous adoption strategy. A sequential adoption strategy (e.g., investment in human capital or ICT first and organizational adaptation after) is more likely not only for the difficulty of managing a simultaneous adoption strategy but also because in the short term there may be weak incentives to introduce significant organizational change. Unlike large firms, small firms do not have to introduce more flexible organizational settings to adapt to ICT. In the long run they may have to adopt a more rational, formal division of labour to take advantage of new ICT systems like ERP or SCM; but in the short run it is likely that specific skilled individuals rather than organizational structures will be directly affected by the new technology.

Table 12. Distribution of firms by cluster

V_{ijk}	Total sample (n=540)	Small firms (n=330)	Medium firms (n=159)	Large firms (n=51)
V111	6.30%	5.15%	5.66%	15.69%
V110	13.52%	13.64%	11.32%	19.61%
V101	6.48%	4.85%	10.06%	5.88%
V011	5.56%	4.85%	7.55%	3.92%
V100	9.81%	10.91%	8.18%	7.84%
V010	17.04%	20.00%	11.95%	13.73%
V001	15.56%	13.03%	20.13%	17.65%
V000	25.74%	27.58%	25.16%	15.69%
	100.00%	100.00%	100.00%	100.00%

Note: In V_{ijk} *i* stands for the value of the dummy for *ICT stock per employee*, *j* stands for the value of the dummy for *HIGHMIDSKILL*, and *k* stands for the value of the variable *ORG*.

To test for pair-wise complementarity, the three productivity equations in levels were run with the inclusion of four clusters corresponding to different states of adoption of co-inventions. The dummies that account for the choice of the three co-inventions altogether were also entered. To control for heterogeneity we have included 21 sector dummies (2-digit ATECO industry codes) and 4 location dummies[19]. The estimation results for these systems of clusters on the whole sample are shown in equations 1 to 3 of Table 13 (definitions of clusters are reported in the same Table).

The coefficients of the dummies S_{11}^{i}, i=1,2,3 are all positive and significant, suggesting that adopting pairs of inventions is always good for productivity. The result of the F test for complementarity is consistent with the hypothesis of complementarity between ICT investment and skills (equation 1). The effects produced by the joint adoption of organizational change and skills (equation 2), and ICT and organization (equation 3) respectively are not strong enough to reach conventional levels of significance of the F test.

From the interaction of the dummies of the three co-inventions together we obtained eight clusters. We are interested to see whether the marginal productivity from the adoption of a pair of strategies increases with the adoption of a third strategy. Therefore we ran three separate tests for relative increases in marginal productivity. In order to provide support to the hypothesis of *organizational complementarity* the inequalities (4) must pass simultaneously the F-test.

The results show that the marginal productivities of all pairs of complements increase with the adoption of the remaining complement. However, this result is not significant for the case where we measure the effect of organizational change on the productivity gain of ICT and skills (first test of equation 4). This result is in line with the estimation results for production function with interaction terms (Tables 9 and 10). Both estimations provide evidence in favour of pair-wise complementary between the strategies, but fail to offer strong support to the *organizational complementarity* hypothesis. We performed the same tests on the sub-samples of small and medium firms (equation 5 and 6). In the case of medium firms the dummies for clusters corresponding to the adoption of pair of complements have positive coefficients while those corresponding to the simultaneous adoption of the three complements have a negative, albeit insignificant, coefficient. This is also in line with the results obtained with the inclusion of interaction terms in the production function approach (Tables 9 and 10).

Table 13. Production function estimations with clusters of complements

	LogVA 2000	LogVA 2000	LogVA 2000	LogVA 2000	LogVA 2000	LogVA 2000
I	(1)	(2)	(3)	(4)	(5) Small firms	(6) Medium firms
Constant	0.773***	0.718***	0.790***	0.786***	0.469	1.641***
	(0.100)	(0.098)	(0.103)	(0.100)	(0.319)	(0.364)
Log NonICT stock 2000	0.054***	0.053***	0.050***	0.054***	0.038*	0.136***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.027)
Log Labor Cost 2000	0.923***	0.927***	0.908***	0.923***	0.993***	0.717***
	(0.025)	(0.026)	(0.028)	(0.025)	(0.060)	(0.055)
ORG1 1997	0.060*					
	(0.036)					
ORG2 1997	0.032					
	(0.028)					
HIGHMIDSKILL 1997		0.050				
		(0.058)				
LogICTinv 1997			0.030**			
			(0.014)			
S^i_{11}	0.112***	0.152***	0.089**			
	(0.037)	(0.038)	(0.045)			
S^i_{10}	0.009	0.063*	0.036			
	(0.032)	(0.035)	(0.029)			
S^i_{01}	-0.049	0.044	-0.010			
	(0.035)	(0.031)	(0.034)			
V_{111}				0.161***	0.129	-0.015
				(0.062)	(0.100)	(0.133)
V_{110}				0.087**	0.056	0.230***
				(0.047)	(0.063)	(0.087)
V_{101}				0.085	0.017	0.037
				(0.039)	(0.060)	(0.064)
V_{100}				-0.032	0.025	-0.192**
				(0.044)	(0.054)	(0.093)
V_{011}				0.028	0.014	0.010
				(0.055)	(0.060)	(0.085)
V_{010}				-0.079**	-0.082	-0.094
				(0.043)	(0.055)	(0.067)
V_{001}				0.004	0.006	0.057
				(0.036)	(0.047)	(0.063)
Controls:						
Ateco sector	YES	YES	YES	YES	YES	YES
Geographical Area	YES	YES	YES	YES	YES	YES
F test	$S^i_{11} = S^i_{10} + S^i_{01}$, $i = 1,2,3$			$V_{111} = V_{110} + V_{001}$		
F	7.32	0.72	1.26	0.082	0.31	1.29
p-value	0.007	0.397	0.261	0.365	0.580	0.259
F test				$V_{111} = V_{101} + V_{010}$		
F				3.69	0.53	0.07
p-value				0.055	0.467	0.786
F test				$V_{111} = V_{011} + V_{100}$		
F				3.39	2.53	0.93
p-value				0.066	0.113	0.336
R2	0.940	0.939	0.938	0.940	0.771	0.832
N	540	540	540	540	330	159

Notes: Mean values of the corresponding continuous variables in 1997 were used to create dummies
Column (1):
S_{11}: dummy for *ICT stock per employee* = 1; dummy for *HIGHMIDSKILL* = 1;
S_{10}: dummy for *ICT stock per employee* = 1; dummy for *HIGHMIDSKILL* = 0;
S_{01}: dummy for *ICT stock per employee* = 0; dummy for *HIGHMIDSKILL* = 1;
Column (2):
S_{11}: dummy for *ICT stock per employee* = 1; *ORG* = 1;
S_{10}: dummy for *ICT stock per employee* = 1; *ORG* = 0;
S_{01}: dummy for *ICT stock per employee* = 0; *ORG* = 1;
Column (3):
S_{11}: *ORG* = 1; dummy for *HIGHMIDSKILL* = 1;
S_{10}: *ORG* = 1; dummy for *HIGHMIDSKILL* = 0;
S_{01}: *ORG* = 0; dummy for *HIGHMIDSKILL* = 1;
Column (4):
In V_{ijk} *i* stands for the value of the dummy for *ICT stock per employee*, *j* stands for the value of the dummy for *HIGHMIDSKILL*, and *k* stands for the value of the variable *ORG*.

In synthesis, our results are robust to different econometric methods and model specifications. They point out that complementary differs across large, medium and small firms. In small firms organizational change associated with either ICT or human capital investments does not produce any effects on firm productivity. Although almost 30 percent of small firms have tried some organizational change, the limited scale of operations reduces the scope for productivity improvements based on formal organizational changes.

Organizational change yields insignificant marginal productivity gains for medium sized firms as well. In this case we find some weak evidence in favour of the SBOC hypothesis.

Overall, we find a strong evidence of complementarity only between ICT and skills.

The joint adoption of the three co-inventions has a negative effect on firm productivity. In particular, we have seen that in medium-sized firm the introduction of organizational change reverses the ICT-human capital complementary effect on productivity. Apparently, then, the costs of innovation tend to increase when different dimensions of the organization are involved in the process of change. And our findings suggest that these costs overcome the benefits. This escalation of organizational costs calls our attention to a ‘classical’ tension between stability and modification of organizational routines. As Nelson and Winter have noted, “the routinization of activities in an organization constitutes the most important form of storage of the organization’s specific operational knowledge” (Nelson and Winter, 1982 p. 99) and the basis for building the organizational capabilities. However, routines can be a source of organizational inertia when the firm has to solve unexpected problems or to undertake simultaneously different avenues of change such as ICT, skills and organizational change. Large innovative firms possess strong meta-routines or dynamic capabilities that help to anticipate the change. However, even successful firms often fail to adapt rapidly to,disruptive innovations, i.e., changes that make existing routines and capabilities obsolete (Christensen and Rosenbloom, 1995; Henderson and Clark, 1990). Even more puzzling is the case of firms who undertake continuous changes in their organizational routines which result in negative performance outcomes. A case in point is constituted by Lockheed, whose policies of continuous internal labour mobility and other related innovative strategies adopted in the production of the L-1011 TriStar contributed to reduce labor productivity of 40-50% per year (Benkard, 2000).

As mentioned before, the timing of the multidimensional innovation process may accounts in part for this paradox. Our results suggest that inertia and a limited absorptive capacity call for an incremental, gradual adoption of multiple co-inventions as opposed to a strategy of contemporaneous adoption. This is not in contrast with the theory of organizational complementarity which does not make any assumption about the sequence of adoption of different co-inventions.

Our data cannot clearly answer the question as to whether large firms have a comparative advantage versus their smaller counterparts in the introduction of a cluster of complementary innovations. In theory large firms have probably a greater absorptive capacity compared to smaller firms but they may suffer from greater organizational inertia. Moreover, smaller firms may need a longer time to learn how to manage (and benefit from) a complex cluster of complementary innovations. This may explain why we observe a decline of the marginal productivity of ICT with the increase in the intensity of skills in medium firms which have introduced organizational change.

An important implication of this discussion is that assessing the impact of multiple innovation strategies on productivity requires a long time window. The shortness of our panel does not allow to study the intertemporal adoption of complementary strategies and their long run productivity effects. A full test of the organizational complementarity hypothesis will be carried out in our future research. A longer panel will allow to see whether medium firms that gradually introduce innovations have the possibility to learn by experimenting different dimensions of organizational change without completely disrupting existing routines.

6. Conclusions

This paper provides new empirical evidence on the relationships among ICT, skills and organizational change at the firm level. Our results overall provide strong support to the skill-biased technical change hypothesis and limited support to the skill-biased organizational change hypothesis. Results concerning more complex interactions between skills, organizational change and ICT (organizational complementarity) are less clearcut.

Our analysis shows that there are strong correlations among these innovation activities, even when using different measures of the same activities.

In line with earlier works, we analysed complementarity in the context of the production function by estimating the marginal effects of the hypothesized complements, their pair-wise interactions, and triple-wise interactions. We found strong evidence in favour of the complementarity hypothesis between ICT and human capital when estimating the productivity equation both in levels and in differenced form. When entered in the same specification together, the interaction terms for ICT-HK and OC-HK relationships appear to be positive. When the three-variable interaction term is entered in the regressions estimates show that the two complementarity effects are not independent from each other: investing in any of the three innovation activities decreases the complementarity effect between the other two.

To further explore the interactions between these three choice variables in the context of a production function we grouped the sample firms and obtained different clusters each representing different combinations of the hypothesized complements – from the full combination (high ICT stock, high level of skills, and intensive organizational changes), which corresponds to the ‘modern’ system of production, to the total absence of co-inventions, which represents the ‘traditional’ system of production. We performed several tests that provided further support to the ICT-HK complementarity hypothesis.

Our findings are only in part consistent with the complementary theory elaborated by Milgrom and Roberts (1990) and the hypothesis of organizational complementarity between ICT and skills developed by Bresnahan (1999) and Bresnahan *et al* (2002). According to the organizational complementarity hypothesis only the full combination of co-invention should produce significant productivity gains at the firm level, whereas intermediate combinations should not produce significant benefits to the firm. We found a positive but insignificant effect of the adoption of the three innovations together in large firms only. For small and medium firms we found evidence of substitution rather than complementarity among the three innovation activities. Future research then should analyze more carefully organizational complementarity in firms of different size.

Despite the richness of the dataset used, our findings are limited by some data shortcomings that it is worth to mention. First, like in many earlier studies, our organizational change variables do not measure accurately the nature of organizational change that the theory indicates as a complement of ICT and skills, namely de-layering of hierarchy and adoption of new forms of division of labour like job rotation and total quality management.

Second, the study of complementarity in the context of the production function implies that we analyze the effects of different strategies on the best level of efficiency that is potentially attainable by the firm with a given production technology. However, the productivity effects of a new cluster of co-inventions take long time to materialise. Even if a firm adopted all the complements (ICT, skills and organizational co-inventions) it may have to learn how to manage the new production system before it will be able to fully enjoy the productivity gains arising from the new production systems. With panel data over a longer time span short-term differences in adaptation costs should evaporate. Moreover, with a longer panel the productivity effects of transitions from one cluster to another could be analyzed. The availability of longer panel data in future research will allow to employ dynamic panel techniques to better account for the potential lagged productivity effects of the joint use of complementary inputs at the same time controlling for non-serially correlated time-variant heterogeneity.

Although our analysis is far to be definitive, our results suggest that the test for the complementarity hypothesis requires a deeper understanding of the multiplicity of interactions between the hypothesized complements in different organisational environments and in particular in firms with different size.

Finally, further analysis should be done in explanation of actual drivers of complementarity looking at more detailed data on firm-specific characteristics (Cassiman and Veugelers, 2002)

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[1] For a comparison of country-level evidence on labour productivity and ICT see Daveri (2003). For country-level studies of the productivity gain of ICT in different sectors see Gambardella and Torrisi (2001) and Fabiani et al (2005).

[2] A major drawback of this measure of technical change is that it cannot distinguish R&D from other activities such as marketing neither it can disentangle the role of ICT from other innovations.

[3] For a survey of the literature on technological change and skills in Italy see Nicita and Torrisi (1999).

[4] Following a popular classification in the ICT industry, Bresnahan (1999) distinguishes among three types of computer use: i. Organizational computing, such as corporate accounting and transaction processing systems, which affect various levels of corporate and departmental administrative processes (e.g., ERP and MRP); ii. Scientific-technical computing (e.g., client-server technical applications like CAD/CAE and CAM), which is mostly targeted to specific departments; iii. Individual productivity computing like word-processing.

[5] Athey and Stern (1998) review different econometric methods for testing theories of complementarity and provide an evaluation under alternative assumptions on the economic and statistical environment.

[6] We have also performed the reduced-form estimations of the investments in each of the potential complements conditional upon the adoption of other complements and controlling for other observable characteristics of the adopter. The results appear to be consistent with SBTC and SBOC hypotheses and could be found in Giuri, Torrisi and Zinovyeva (2005).

[7] Unlike the estimator originally developed by Heckman to deal with the selection of the dependent variable (productivity), the treatment effect model focuses on the selection of an independent variable. In this context, the selection problem is treated as an omitted variable problem and all cases (zero and non-zero ICT expenditures) are included in the second stage.

[8] This inequality reveals the existence of complementarity in relative terms, in that the two practices are complements also if the right hand side and the left hand side of the inequality are negative and the left hand side is greater than the right hand side. This suggests that the marginal change from LH to HH is always better than the marginal change from LL to HL. If the two practices are complements, LL could in principle be better than HL.

[9] The use of different thresholds such as the median (which is the thresholds chosen on the basis of the analysis of kernel density) yielded similar results as those presented in the paper. For simplicity, in Section 5 we report only the results based on the clustering procedure that uses the mean value as a threshold.

[10] A similar methodology was used by Leiponen (2005) for the test of complementarity between skills, innovation and R&D collaborations on a sample of Finnish firms and by Arvanitis (2005) for the test of complementarity between ICT, skills and human capital in a sample of Swiss firms. In our estimations s_{00}^{h} (non-adoption) was normalized to zero.

[11] Our sample was constructed by removing observations with zero ICT investments in one of the two waves and missing values for key variables in our analysis. Sample size and composition have been obtained by the Neyman formula which allows to minimize the sample error. Data for firms with over 500 employees cover the population of manufacturing firms. The questionnaire on qualitative information contains sections on investments, R&D, internationalization and labor forces. For details on the survey design see the report of Capitalia (2002), available in Italian at the following website http://www.capitalia.it/dwload/studiericerche/INDAG_MANIFATT_RAPPORTO_8.pdf (April 2005).

[12] This was done for comparison across different models. In some models, due to missing values, we were forced to work with even smaller subsamples. We performed one-sided tests of means which suggested that firms in our subsample are not different from the rest of observations in terms of size, human capital variables, and technical stock proxy. Omission of observations with no ICT investments, however, makes the subsample biased towards firms that have introduced product and process innovations, performed R&D, and experienced organizational change. To estimate sample selection models we used slightly larger samples. Moreover, for each model we have also performed estimations on the largest possible sample. In all regressions of this kind the estimates appeared to be not significantly different from the ones obtained from equivalent estimation on the reduced sample. The complete set of estimation results is available upon request.

[13] It is worth to remind that, according to the Italian Statitical Institute (ISTAT), 98% of Italian firms have between 1 and 49 employees and about 56% of firms are located in North Italy. Our sample then overrepresents medium and large firms located in Northern regions. At the same time, we decided not to adopt probability weighted estimation techniques because in about 37% of strata identified by Mediocredito Centrale we have at most one observation in our final sample.

[14] Piva and Vivarelli (2004) and Piva *et al* (2005) proxy the level of skills by occupational variables, namely, the number of blue-collar and white-collar workers. They argue that these indicators of skills should be preferred in the context of a production function approach as they reflect the dynamics of labor demand. By contrast, indicators based on the level of education capture the dynamics of labor supply. However, changes in the occupational mix are closely related to organizational change, such as introducing a more modular organizational structure. The use of occupational variables along with organizational change then may lead to multicollinearity problems. Moreover, as Piva and Vivarelli notice, the OECD has found that occupation and educational level are strongly correlated, especially in the manufacturing sector.

[15] See Caroli and van Reenen (2001), Bresnahan *et al*. (2002), Greenan (2003), Berthschek and Kaiser (2004).

[16] We should remind that capital goods are a typical channel of embodied technical progress especially in traditional sectors.

[17] To see whether the interaction patterns between the three choice variables change across different production systems we estimated the models above on the sub-samples of firms operating in different Pavitt sectors (results not shown). The results are very similar to estimates obtained on the full sample. This suggests that the substitution/complementarity effects discussed above are firm-specific rather than sector-specific. These results, however, are very preliminary and should be considered with caution. More detailed sector study is required to reach clear-cut conclusions.

[18] Recall that for ICT and skills the 0 code in the cluster does not necessarily mean 'no adoption' but instead low-intensive adoption of the strategy (below the mean). For organizational change only '0' indicates no adoption and 1 indicates adoption of organizational change related to either product or process innovations.

[19] To control for within-sector heterogeneity we have also entered a variable that measure the share of blue collars in total occupation. The effects of clusters are robust to this control (not shown).