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Technological and Organizational Changes as Determinants of the Skill Bias: Evidence from the Italian Machinery Industry

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Recent empirical literature has introduced the 'Skill Biased Organizational Change' (SBOC) hypothesis, according to which organizational change can be considered as one of the main causes of the skill bias (increase in the number of highly skilled workers) exhibited by manufacturing employment in developed countries. This paper focuses on the importance of the SBOC with respect to the more traditional 'Skill Biased Technological Change' in driving the skill composition of workers in the Italian machinery sector. A dynamic panel data analysis is proposed which uses a unique firm-level dataset. The results show that both skilled and unskilled workers are negatively affected by technological change, while organizational change—which in turn may be linked to new technologies—is positively linked to skilled workers. **Copyright © 2005 John Wiley & Sons, Ltd.**

INTRODUCTION

In most developed countries the share of skilled workers has increased in recent decades. The economic literature has proposed an explanation for this empirical regularity based on the so-called 'Skill Biased Technological Change' (SBTC) hypothesis, that is, the non-neutrality of technological change. On this hypothesis, acceleration in the rate of technological change produces an increase in the demand for skilled labor and a decrease in the demand for unskilled workers.

Whilst SBTC appears to be a long-term historical trend (see Nelson and Winter, 1982; Goldin and Katz, 1998), the diffusion of Information and Communication Technologies (ICT) seems to have given new impetus to the substitution of unskilled workers with skilled ones. However, given that at the industry level the evidence for this acceleration is rather mixed, with some industries displaying faster upskilling levels and higher skill premia (see Autor *et al.*, 1998), one might conclude that there is also a 'differential industry effect' of new technologies (Jones, 1965).[1]

However, some researchers have attempted to explore other possible alternative/complementary explanations for the skill-bias. For instance, trade economists maintain that upskilling also depends on *globalization*,[2] whereas industrial and managerial economists contend that it is also due to processes of *reorganization of production* ('Skill Biased Organizational Change', in so far SBOC).

This paper will test the SBTC and the SBOC hypotheses on a sample of firms operating in the

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Italian machinery sector. It is organized as follows. The following section discusses the economic literature on the role of technological and organizational changes as possible explanations for the skill bias. The next section gives an overview of the machinery industry in Italy, while we further set out our empirical analysis based on a balanced panel of 22 (large) firms in the Italian machinery industry. Finally, some concluding remarks are made.

THE SBTC AND SBOC HYPOTHESES

Skill Biased Technological Change

The SBTC hypothesis is based on the well-established idea that there is close complementarity between new technologies and skilled workers in that only the latter are fully able to implement these technologies. Empirical studies testing this hypothesis, at both the firm and industry level, have been carried on to manufacturing sectors in various developed countries. The proxies used to measure technology can be grouped into three categories: inputs to the knowledge production function (R&D expenditure); outputs from the knowledge production function (patents); diffusion of innovative outputs throughout the economy (office machinery, computer capital, production-based technologies) (for a discussion of the advantages and disadvantages of these various proxies, see Chennells and Van Reenen, 2002).

As far as the US is concerned, there is abundant evidence to support the SBTC hypothesis. Among the most representative papers, Berman *et al*., (1994)—at the industry level—and Dunne *et al*. (1996)—at the firm level—find a positive and significant relationship between R&D and skilled labor in US manufacturing. Doms *et al*. (1997)—for firms in selected US industrial sectors—show that the use of the most advanced industrial technologies gives rise to greater employment of workers with higher qualifications. Moreover, Siegel (1998) finds evidence of upskilling in Long Island manufacturing plants that had introduced new technologies. Finally, Adams (1999) has analyzed US chemical firms to show the skill bias nature of R&D expenditure and innovative investments.

In Canada, both Betts (1997), who focused on manufacturing and Gera *et al*. (2001), who analyzed both the manufacturing and service sectors (1981–1994), show a connection between various measures of technology and the growing demand for skilled workers.

For the UK, Machin (1996)—using both sector-level and firm-level data in the 1990s—and Haskel and Heden (1999)—at the firm level—respectively, show a positive relation among R&D intensity, number of innovations produced and used, and skilled labor (in the sector analysis), and between the use of computers and skilled labor in the case of firms in both studies.

The results of studies regarding other countries generally confirm the SBTC hypothesis, although they are less robust than they are for the British and North American economies. In France, for example, Mairesse *et al*. (2001) obtain results similar to Machin's for firm data where the technological variables are ICT capital and ICT workers; however, only the negative relation between ICT and less-qualified labor is robust in time-series. This confirms Goux and Maurin's results (2000) showing that the increased spread of new technology accounts for only 15% of the change in labor demand in France between 1970 and 1993.

Skill Biased Organizational Change

Skill Biased Organizational Change (SBOC) is a specific form of innovation which might be complementary rather than alternative to technological change. In this respect, the SBOC hypothesis relies on the recent idea that there is a progressive *organizational* transformation within firms whereby they move from rigid, Tayloristic-style, segmented forms of organization towards more flexible and 'holistic' ones (see Lindbeck and Snower, 1996). This phenomenon first appeared in the US and Japan and has since spread through Europe (see Aoki, 1986; Greenan and Guellec, 1998; OECD, 1999). It is impossible here to give a full account of the vast body of literature on organizational change and its impact on a firm's structure and performance.[3] Nevertheless economic, management and sociological studies on the subject seem to single out three main trends (Caroli, 2001): (i) *Decentralization and delayering*, which implies 'lean production' associated with such new firms' functions as just-in-time,

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management of breakdowns, and quality control, which in turn imply both the decentralization of decision-making and greater involvement, responsibility and autonomy on the workshop floor (see Brynjolfsson and Mendelson, 1993); (ii) *Collective work*, that is, new work practices such as work teams and quality circles which require collective effort by labor (see Osterman, 1994); (iii) *Multi-tasks*, as a consequence of which workers are now required both to perform a greater variety of tasks within a given occupation and to rotate among different jobs (see Greenan and Mairesse, 1999; Ichniowski and Shaw, 2003).

The few empirical analyses available generally use dummy variables related to the introduction of organizational changes, delayering, intensity of communication within the workplace, and autonomy of workers.

These organizational innovations entail an upskilling of the manufacturing workforce. Using a French survey on work organization, Greenan and Guellec (1998) find that organizational changes—such as greater worker autonomy and increased between-workers communication—are positively correlated with skill upgrading. Moreover, Caroli and Van Reenen (2001) have compared two panels of French and British firms, focusing on organizational change measured with a dummy. Their results support the SBOC hypothesis and prove to be econometrically significant in both the panels.

The empirical literature also reveals that most organizational changes occur simultaneously, assuming the form of 'clusters' of organizational innovations. For instance, Ichniowski *et al.* (1997) show the complementarity of the introduction of teamwork, flexible job assignment and intensive worker–management communication in US steel manufacturing.

Finally, a recent strand in the literature tends to emphasise that technological change and organizational change are complementary.[4] They often generate super-additive effects in terms of a firm's performance, measured either in terms of productivity or profitability (see Pavitt *et al.*, 1989; Milgrom and Roberts, 1990, 1995; Black and Lynch, 2001[5]).

In Italy, Piva *et al.* (2005) identify a super-additive effect of technological and organizational change[6] on the skill composition of Italian manufacturing employment in the 1990s. In particular, they show (a) that the alleged role of R&D alone in determining skill bias is not confirmed by econometric estimations, (b) that significant organizational changes made by a firm to its structure and functions are major factors affecting skill composition, and (c) that combining the R&D and the organization variables yields higher and more significant coefficients, even in comparison with the organization variable in previous estimates.

THE MACHINERY INDUSTRY IN ITALY

Italian manufacturing is to a large extent characterized by the use of intermediate technologies. The machinery industry[7] embodies technological change and is one of the main sources of new technology for other industries adopting new capital equipment. Besides driving technological change and innovation in traditional industries—the core of the Italian economy—this industry is one of the few with a competitive advantage deriving from its own technological strength. Consequently, Italy is among the top exporters worldwide of specialized industrial machinery, with a share of world exports almost always above 10% during the 1990s (with a peak of 11.51% in 1996), and a share of EU exports ranging between 21 and 22% over the same period (with a peak of 22.6% again in 1996).

Data reported in Table 1 for the 1991–2000 period provide an overview of the structure and the performance of this industry.[8] Firstly, the data show a significant process of new firm formation in the last decade (total number of firms increases by nearly 39%). In particular, net entry grew stronger over the second half of the decade, when the total number of active firms in the industry increased at a rate of between 6.19% (in 2000) and 8.25% (in 1996). However, Italian firms in this industry were also characterized by an aggressive investment strategy (with total fixed investments increasing by an average yearly rate of more than 3% during the period). New firm formation and accelerating investments generally imply both embodied technical change and reorganization of the workshop floor, suggesting that technical progress and organizational change may have played an important role in reshaping the composition of the sectoral workforce in favor of skilled workers, at least in the second half of the 1990s.

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Table 1. Structure and Economic Performances of Italian Firms in the Machinery Industry (291 and 292 sectors—ISIC rev.3)[a].

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Number of firms	2339	2328	2316	2304	2292	2481	2671	2861	3051	3240
−Δ No. of firms (%)		−0.47	−0.52	−0.52	−0.52	8.25	7.66	7.11	6.64	6.19
Number of employees	283 314	272 345	260 618	261 090	267 679	272 691	272 380	272 943	269 796	287 735
−Δ No. of employees (%)		−3.9	−4.3	0.2	2.5	1.9	−0.1	0.2	−1.2	6.6
Average firm size	121.12	117.01	112.53	113.33	116.79	109.89	101.96	95.39	88.43	88.79
Total sales (M)	33 683	35 236	36 653	39 936	47 511	50 333	52 184	54 219	54 495	60 020
−Δ Total sales %		4.6	4.0	9.0	19.0	5.9	3.7	3.9	0.5	10.1
Gross operating surplus (%)	9.7	9.9	10.6	10.7	10.1	9.4	9.8	9.9	10.1	10.5
Net income (%)	2.5	2.1	2.3	2.8	3.3	2.5	2.3	2.5	2.5	2.0
Fixed investments (%)	3.2	2.6	2.5	2.6	4.8	3.8	3.2	3.1	3.4	5.0
Fixed capital intensity (%)	16.3	17.0	16.8	15.9	14.6	15.6	16.7	17.5	18.5	18.7
Total capital intensity (%)	76.2	75.6	72.8	68.7	65.0	67.2	68.4	70.2	73.1	69.5
Leverage (%)	1.13	1.09	1.04	1.00	0.96	1.04	1.03	1.06	1.07	0.95
ROE (after tax)	10.7	8.4	9.4	12.1	15.5	11.7	10.6	11.4	10.7	8.3

Source: Prometeia Srl.
[a] All monetary values are in current prices.

Table 1 furnishes only one direct indication concerning employment, namely a general stability of total employment during the 1990–2000 period, with a significant reduction in the early 1990s and a marked increase from 1999 to 2000.

Analysis of the economic performance yields a generally positive picture. The dynamics of total sales were particularly favorable throughout the 1990s, with a peak in 1995, when total sales in current prices grew by nearly 20% compared with the previous year. Also gross operating surplus, net income, and ROE were positive, again with a peak around the mid-1990s. Good profitability can also be considered a pre-condition for technological updating both in terms of available resources and positive economic expectations.

DATA AND EMPIRICAL ESTIMATES

Data

Larger firms are more likely to be involved in technological and organizational changes than their smaller counterparts (see Brouwer and Kleinknecht, 1996; Cohen and Klepper, 1996; Colombo and Delmastro, 1999). Therefore, our empirical analysis began by identifying the 200 largest firms[9] in the machinery industry. These firms, located mostly in Northern and Central Italy, were interviewed via e-mail, or when an e-mail address was not available or replies were not forthcoming after four weeks, by means of a postal questionnaire. Although only 25 of the firms (12.5%) returned the questionnaire, it was possible to construct a balanced panel database covering the six-year period between 1996 and 2001 for 22 of them.[10] Firms responding to our questionnaire were thus approximately 1% of the total number of firms in the industry, accounting for nearly 3% of total employment and sales. The firms in our sample were larger in terms of number of employees per firm and sales than the average values for the industry (253 was the average number of employees per firm in our sample, 110 was the value in the industry in 1996; approximately 61 million Euro was the average value of sales in our sample, 20 million Euro was the value in the industry in 1996).

Besides standard information on their size, sales, capital, and belonging/not belonging to an industrial group, firms were requested to provide detailed data and information on the composition of their workforces, labor costs, patents registered with either USPTO or EPO, R&D expenditures, purchases of embodied (machinery and capital equipment) or disembodied (licenses) technological innovations. In the concluding section of the questionnaire, firms were requested to indicate the business functions[11] where organizational innovations had been introduced in each of the six years and, if they had introduced such innovations, to quantify the percentage of the workforce involved. With reference to skills, our data enabled us to identify two broad categories of homogeneous workers: white collars (WC,

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including the entrepreneur and family assistants, senior and junior managers, and office workers) and blue collars (BC, manual workers).

Methodology

The econometric specification was conducted within a rather standard theoretical framework based on the transcendental logarithmic (or translog) firm cost function originally introduced by Kmenta (1967) and formally developed by Christensen *et al.* (1971, 1973).

The method was based on estimation of a restricted variable cost function given only by the cost of labor (the only variable factors of production are the two categories of workers) while capital and technology/organization are assumed to be quasi-fixed factors for firm i

$$LC_i = f(Y_i, K_i, w_{ij}, SB_i), \quad (1)$$

where: LC is the labour cost, f the translog functional form, Y the output, K the capital, w_j the wage for the jth category of workers (in our case $j = 2$: WC is the white collars, and BC the blue collars), SB the possible sources of skill bias, namely technology and/or organization.

With all the variables in logarithms, minimization of costs and implementation of Shephard's lemma at time t yields:

$$s_i = \frac{\partial \ln LC_i}{\partial \ln w_{i,WC}} = \varphi_i + \alpha \ln(Y_i) + \beta \ln(K_i) + \gamma \ln(w_{i,WC}/w_{i,BC}) + \delta \ln(SB_i) \quad (2)$$

where s_i represents the share of labor cost of white collars (the blue collar equation is complementary to one and has to be dropped).

In this specification, the relative wage variable carries a risk of endogeneity—due to its collinearity with the dependent variable—and it is generally eliminated or instrumented (see Anderton and Brenton, 1999; Chennells and Van Reenen, 2002). However, the specification proposed in (2) can be proxied by using employment data (Bartel and Lichtenberg, 1987), and in this case the dependent variable can be measured either as the ratio of white collars to total workers or the ratio of white collars to blue collars.[12]

Nevertheless, in order to test the effects of technological change and/or organizational change on both categories of workers, two separate equations can be estimated, one for white collars and one for blue collars. In this framework, the dependent variables (*WC* and *BC*, respectively) are taken in absolute values and not as a share of total employment, and the impact of SBTC and SBOC is checked for output, capital and labor costs, as in Equation (2).

Technological change (TEC) was measured for each year as the total investment in innovation, including R&D, purchase of embodied and disembodied technology and adoption of ICT; organizational changes (OC) was measured yearly as the number of employees involved in reorganizational processes in the firm's production activity[13] (the first macro business function). The most commonly adopted organizational changes introduced by responding firms ranged from reorganization of production processes (logistics included) to adoption of quality control procedures.[14]

Also the interaction between technological innovation and organizational change (TEC*OC) was taken into account, the purpose being to test the hypothesis of a possible super-additive relationship between new technologies and organizational practices (Pavitt, 2002). Moreover, in order to control for the dynamic path of the dependent variable, which turned out to be rather persistent in its time dimension (for both WC and BC), the lagged dependent variable was included in the right hand-side of each of the two equations (Equation (3) for WC and Equation (4) for BC)

$$\ln(WC)_{it} = \alpha \ln(WC)_{i,t-1} + \beta \ln(Y_{it}) + \gamma \ln(K_{it}) + \delta \ln(W_{WC,it}) + \zeta \ln(SB_{it}) + u_{it}, \quad (3)$$

$$\ln(BC)_{it} = \tilde{\alpha} \ln(BC)_{i,t-1} + \tilde{\beta} \ln(Y_{it}) + \tilde{\gamma} \ln(K_{it}) + \tilde{\delta} \ln(W_{WC,it}) + \tilde{\zeta} \ln(SB_{it}) + \tilde{u}_{it} \quad (4)$$

where Y denotes sales, K capital, W wages (there is no more need to instrument the wage regressor), SB skill bias variable alternatively indicating TEC, OC, and TEC*OC.

The inclusion of the lagged dependent variable in a dynamic panel data context requires adequate econometric techniques, owing to the correlation between the lagged dependent variable and the error term (Baltagi, 2001, p.129). Indeed, this correlation renders the Ordinary Least Squares estimator (OLS) definitely biased and inconsistent, while the Within Group estimator (WG) may be biased, and also inconsistent if the time dimension is not large enough (as in our case). In order to achieve better econometric performances, it is first

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necessary to get rid of individual firms' effects (a component of the error term). First difference transformation is then implemented, and instrumental variable techniques are used to instrument new regressors correlated with new error terms. In particular, Arellano and Bond (1991) propose the unbiased and consistent GMM-DIF estimator (first differenced) which uses an instrument matrix containing instruments for all the regressors depending on the assumptions made about endogeneity, predetermination and exogeneity of the corresponding instrumented variable.[15]

Although we were aware that the GMM procedure is better suited to large panel—and that given our small sample size it might have yielded biased results like the WG estimator—we decided to put forward this attempt and test its validity. However, as shown by Andersen and Sørensen (1996), a GMM estimate using a small panel must be characterized by a limited number of moment conditions (see notes in Tables 2 and 3 below).[16]

Empirical results

We ran separate regressions for white collars (Equation (3), Table 2) and blue collars (Equation (4), Table 3) testing the SBTC, the SBOC, and the joint SBTC/SBOC hypotheses and comparing the WG with the GMM-DIF estimators.

GMM-DIF can be regarded as better than the WG estimator if the autocorrelation test and the Sargan test of over-identifying restrictions are both passed.[17] In the white collars equation the GMM-DIF was always better than the WG regression; in the blue collar equation the WG was instead more reliable than the GMM-DIF estimator (in fact, autocorrelation tests were not passed even if the Sargan test did not reject the null hypothesis).

As regards the results, the highly persistent demand for white collars (Table 2) increases—as expected—with total sales and with a reduction of white collars' wages, while investments do not play a significant role. As far as TEC is concerned, the results do not support the SBTC hypothesis—or at least they do not in the GMM-DIF estimation: firms more closely involved in technological change reduce the employment of white collar workers (column 2). Although we are unable to distinguish between the single components of this broad white collar category, it is likely that this result derives from a large extent from a reduction

Table 2. Regression Results: White Collars.

	(1) Within Group	(2) GMM-DIF	(3) Within Group	(4) GMM-DIF	(5) Within Group	(6) GMM-DIF
White collars (−1)	0.75***	0.83***	0.73***	0.68***	0.73***	0.74***
	(11.1)	(5.43)	(10.8)	(4.02)	(10.8)	(5.03)
Sales	0.20***	0.17***	0.19***	0.19***	0.19***	0.17***
	(3.97)	(4.38)	(3.85)	(3.26)	(3.77)	(3.21)
Capital	0.02	0.04	0.02	0.05	0.02	0.04
	(0.61)	(1.43)	(0.56)	(1.00)	(0.58)	(0.97)
Wages	−0.07	−0.23*	−0.08	−0.29**	−0.08	−0.28**
	(0.52)	(1.68)	(0.60)	(2.28)	(0.62)	(2.33)
TEC	−0.06	−0.16**				
	(1.56)	(2.07)				
OC			0.005	0.05*		
			(0.60)	(1.66)		
TEC*OC					0.005	0.02*
					(0.83)	(1.74)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)		−1.74*		−1.71*		−2.19**
AR(2)		−0.01		−0.58		−1.12
Sargan test		11.59		6.91		11.45
Observations	110	88	110	88	110	88

Note: The monetary variables are all expressed in constant prices (base = 1995); the one-step GMM-DIF estimates are in first differences; in brackets: *t*-statistics in absolute value, robust for heteroscedasticity; * = 10% significant, ** = 5%, *** = 1%; in the GMM-DIF estimates lagged white collars, lagged blue collars, TEC, OC and TEC*OC are considered to be endogenous; sales, capital and wages to be exogenous; only three instruments are used in each regression: in fact, using too many instruments for a given cross-sectional sample size in a GMM framework may produce significant finite sample bias (Andersen and Sørensen, 1996; Doornik *et al.*, 2002); AR(1) and AR(2) are tests—with distribution N(0,1)—on the serial correlation of residuals; the Sargan-test has a $\chi^2(16)$ distribution under the null hypothesis of validity of the instruments; DPD DPD 1.00 (Dynamic Panel Data) for Ox was used to run the analysis (see www.doornik.com).

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Table 3. Regression Results: Blue Collars.

	(1) Within Group	(2) GMM-DIF	(3) Within Group	(4) GMM-DIF	(5) Within Group	(6) GMM-DIF
Blue collars (1)	0.57*** 0.39**	0.57***	0.50***	0.57***	0.49***	
	(7.46)	(2.41)	(7.34)	(2.84)	(7.28)	(3.18)
Sales	0.23***	0.18*	0.22***	0.12	0.22***	0.13*
	(3.40)	(1.72)	(3.09)	(1.50)	(3.18)	(1.70)
Capital	0.02	0.10	0.01	0.05	0.01	0.05
	(0.43)	(1.47)	(0.25)	(0.67)	(0.25)	(0.78)
Wages	−0.35*	0.14	−0.33*	−0.14	−0.34*	−0.15
	(1.93)	(0.81)	(1.80)	(0.76)	(1.80)	(0.80)
TEC	−0.11*	−0.41**				
	(1.95)	(2.21)				
OC			0.01	−0.02		
			(1.24)	(0.42)		
TEC*OC					−0.01	−0.02
					(0.69)	(0.91)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)		−1.16		−1.26		−1.61
AR(2)		0.98		0.31		0.14
Sargan test		13.56		15.24		15.60
Observations	110	88	110	88	110	88

Note: The monetary variables are all expressed in constant prices (base = 1995); the one-step GMM-DIF estimates are in first differences; in brackets: *t*-statistics in absolute value, robust for heteroscedasticity; * = 10% significant, ** = 5%, *** = 1%; in the GMM-DIF estimates lagged white collars, lagged blue collars, TEC, OC and TEC*OC are considered to be endogenous; sales, capital and wages to be exogenous; only three instruments are used in each regression: in fact, using too many instruments for a given cross-sectional sample size in a GMM framework may produce significant finite sample bias (Andersen and Sørensen, 1996; Doornik *et al*., 2002); AR(1) and AR(2) are tests—with distribution N(0,1)—on the serial correlation of residuals; the Sargan-test has a $\chi^2(16)$ distribution under the null hypothesis of validity of the instruments; DPD DPD 1.00 (Dynamic Panel Data) for Ox was used to run the analysis (see www.doornik.com).

in the number of clerical workers and intermediate figures, while scientists and skilled technicians are not replaced by new technologies.

Conversely, the SBOC hypothesis is confirmed by the GMM-DIF estimates (even though the coefficient is only barely significant, see column 4): the adoption of new organizational procedures in the production business functions induces an increase in skilled, flexible and multi-tasking workers.

Finally, the TEC*SBOC interaction is found to positively and significantly affect the demand for white collar workers (column 6): new organizational practices interact with technological changes to generate super-additive effects in favor of skilled workers.

Turning to Table 3, the demand for blue collar workers is positively and significantly affected by total sales and negatively influenced by wages; capital is again positive but not significant.

Technological change negatively affects the demand for blue collars, which partly supports the SBTC hypothesis (column 1), while organizational change is substantially neutral (column 3) suggesting that re-organization entailing an increased demand for white collars do not necessarily and simultaneously occur together with restructuring at the shop floor level.

Finally, no statistically significant impact arises from the interaction between technological and organizational change (column 5).

CONCLUSIONS AND MANAGERIAL IMPLICATIONS

Using new data from a sample of firms operating in the Italian machinery sector, we have shown that technological change seems to be more generally labor-saving than skill-biased. In the sector examined, both white collars and blue collars are negatively affected by the adoption of new technologies and investment in innovation. By contrast, organizational change seems to have an asymmetric effect in favor of skilled workers. Finally, the demand for white collars seems to be increased by the super-additive interaction between organization and technology, showing that the positive impact of organizational change is dominant.

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Although these results are specific to the sector examined, they have some interesting managerial implications. First, at least in some sectors, technological change is likely to have an overall labor-saving impact, involving both blue and white collars, with obvious implications for Human Resource Management. Second, organizational change may be skill-biased, implying the need for labor force training and re-training both on and off the job. Third, although no clear-cut evidence for a super-additive effect emerges from this study, the interaction between technological and organizational change seems to be driven by new organizational practices, and it should be monitored carefully, in terms of its impact on both a firm's performance and on the level and structure of employment within the firm.

APPENDIX

The summary statistics for 1996 are shown in Table A1.

NOTES

1. This is important from an empirical point of view: evidence of SBTC should be tested either in a single industry (as in this paper) or with careful control for industrial fixed effects.
2. This strand of literature supports the hypothesis that increased volumes of world trade and FDI have caused a reallocation of the labor force, with unskilled-intensive activities shifting to the least developed countries while skilled-intensive activities remain in the developed ones (Wood, 1994, 1995). Owing to a lack of data, few empirical analyses have tested this hypothesis (see, for example, Slaughter, 2000, for the US, and Piva and Vivarelli, 2002, 2004, for Italy, who do not find strong support for the international explanation of the skill-bias).
3. This literature has focused more on the consequences of organizational change on productivity than on its effects on skill-composition. See, among others, Colombo and Delmastro (2002).
4. New ICT technologies, for example, modify the way in which decisions are made in a firm, often making hierarchies redundant because orders are replaced by interactions among workers (see Bolton and Dewatripont, 1994).
5. Conversely, the mismatch between technological change and organizational inertia may generate an adverse impact on a firm's performance (the so-called 'Solow's paradox'; see Brynjolfsson *et al.*, 1997; Brynjolfsson and Hitt, 2000).
6. The possible interaction between technological and organizational change has been also investigated in case-study analyses; for example, Fernandez (2001)—analyzing the retooling of a food processing plant in the US—shows that organizational and human resources factors have strongly mediated the

Table A1. Summary Statistics—1996

	Mean	Standard Deviation	Average Annual Change (%)
Employment	253	484.15	2.14
White collars	81	104.60	1.79
Blue collars	172	389.39	1.36
Sales (millions of Euro)	60.87	108.44	3.65
Capital (millions of Euro)	28.88	72.67	8.60
White collars wages (000 Euro per employee)	69.31	9.24	0.76
Blue collars wages (000 Euro per employee)	48.86	7.76	0.74
TEC (millions of Euro)	2.17	2.70	4.00
Structural Characteristics (yes/no)			
	Number of firms (yes)	Percentage	
Belonging to industrial groups	11	50%	
Exporting	22	100%	
Foreign Direct Investments	3	14%	
Patenting	14	64%	

Notes: Sales, capital, white collars wages, blue collars wages and TEC are expressed at 1995 prices; The original dataset was unbalanced. In order to obtain a balanced panel, some interpolations were performed by applying to the missing values the average rate of change of the relevant variable—in the available years—for each firm. In particular, one firm had 2 missing values in the blue collars' wages, 2 firms had 2 missing values each in the white collars' wages, 1 firm had 3 missing values in the TEC variable, 6 firms had missing values in OC (2 firms had 4 missing values and 4 firms had 2 missing values).

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impact of changing technology, whereas Pavitt (2002)—analyzing the development of 'innovating routines' inside the firm—shows the importance of the matching of specific corporate competencies and organizational practices to the market opportunities offered by specific technologies.
7. Machinery industry includes sectors 291 (Manufacture of general purpose machinery) and 292 (Manufacture of special purpose machinery)—ISIC rev.3.
8. Data, provided by the research institute Prometeia SRL, cover the entire Italian machinery sector.
9. In the first stage of the research 600 firms were identified, but because we suspected that smaller firms were unlikely to be affected by significant and recordable technological and organizational changes, and also due to financial constraints, only one-third of the initial firms were contacted (the largest ones).
10. See Appendix A for details.
11. Three aggregate macro business functions were considered in the questionnaire: production/logistics/quality, administration/management and sales/marketing.
12. Although less straightforward from a theoretical point of view, the specification in employment shares has been used—either alternatively or jointly with the specification in labour cost shares—by many researchers (see Berman *et al*., 1994; Machin, 1996; Doms *et al*., 1997; Machin and Van Reenen, 1998; Siegel, 1998; Aguirregabiria and Alonso-Borrego, 2001).
13. The other two macro business functions turned out not to be relevant in our sample, therefore they were not included in the econometric analysis.
14. Sample summary descriptive statistics are reported in Appendix A (Table A.1). As will be noted, an upskilling trend is detectable, since the average annual change of WC was 1.79% compared to 1.36% for BC.
15. Accordingly, if the generic $x_{i,t}$ variable is assumed to be endogenous, the lagged values $x_{i,t-2}$ and longer lags are valid instrumental variables in the first differenced equations for periods $t=3,\ldots,T$. If the variable is predetermined, then $x_{i,t-1}$ is additionally available as a valid instrument in the first differenced equation. If the stronger assumption is made that $x_{i,t}$ is strictly exogenous, then the complete time series of the $x_{i,t}$ or the contemporaneous first difference are valid instrumental variables on each of first-differenced equations (see Bond, 2002).
16. Blundell and Bond (1998) have defined a more appropriate and efficient estimator, GMM-SYS, which should be used with dynamic panel datasets when the dependent variable is very persistent. Unfortunately, the low number of observations in our sample, and the large number of instruments required, make the GMM-SYS difficult to implement here (Doornik *et al*., 2002).
17. Autocorrelation test: AR(1) must be significantly negative and AR(2) must not be significant in order to test for lack of second-order serial correlation in the first-difference residuals; Sargan test: the null hypothesis of validity of the instruments must not be rejected.

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