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Effect Of Firm Innovation On Labour Force Csomposition: The Case Of Italian Manufacturing

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Abstract

This paper investigates the causal relationship between innovation and labour force reallocation within the firm, measured as the share of white collar workers. To the extent that intra-firm reallocation can be considered as a substitute for inter-firms and sectors reallocations, innovation activity can be effective in hampering immigration flows from lagging regions to the richest ones. Using data on 5,000 Italian manufacturing firms we provide evidence that where sizable migration flow of graduated people took place the innovation process was not effective in increasing the requirement of high-skill workers.

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1. Introduction

Recent empirical evidence highlights the existence of within-firm margins of adjustment that play a prominent role both along the ups-and-downs of the cycle (Bilbiie et al. 2007, Broda and Weinstein 2007) and in response to competition shocks (Bernard et. al. 2009): creative destruction occurs not only between sectors and firms, but also within the firm. Such intra-firm changes take the form of product-menu renewal (adding and dropping lines of production), changes in production process, management innovation. They generally lead to increase firm-level efficiency and/or the quality content of firm-level production (Bernard et. al. 2010, Mayer et al. 2010). As a form of reaction to business-cycle and competitive shocks, *intra-muros* shifts of resources could be considered as a substitute for inter-firms and inter-sector adjustments. As such, one would expect intra-firm labour reallocation processes of the kind as those observed in the aggregate, both at sector and economy level: within-firm renewal of activities and organization should be accompanied by within-firm renewal of skills. Grounded on this strand of the literature, this paper contributes to the ongoing discussion about skill-biased technological change as an explanation for the observed increase of the share of high-qualified employees in many developed countries (see, e.g. Acemoglu, 2002, for a survey). Actually, it extends the aforementioned literature by emphasising the relevance of within-firm, rather than within-sector, resource shifts. Indeed, we deal with this issue in the case of Italian manufacturing firms. Recent works (De Nardis and Ventura 2010, De Nardis and Pappalardo 2009, Bugamelli et al. 2009) show that intra-firm innovations of product, process and management practices were actually relevant in shaping Italian firms' adjustment to rising competitive pressures in the first half of last decade. The question we want to address is whether such efforts did induce intra-firm labour force composition in the direction of skill-upgrading. To this end we make use of a survey of about 5,000 manufacturing firms observed over the period 2004-06. The aim of the paper is twofold. First we want to detect the existence of a causal effect going from innovation activity to changes in firm-level labour force composition, where the latter is measured by the share of white collar workers over total number of firm's employees. Second, considering the territorial divide characterizing the Italian economy, we want to investigate whether there were territorial differences in such causal link. The regional dimension of the phenomenon is worth exploring because it has direct policy implications. As far as intra-firm labour adjustment works as a substitute for inter-firm and inter-sector reallocation, an innovation-induced rise in high-skill labour requirement of firms in the South could limit the drain of high-skill labour migration from that region towards the North. On the other hand, if it were not effective in the period under scrutiny, the South would suffer from further human capital impoverishment in the following years, making investments in the area even less attractive.

In general, we find evidence that intra-firm labour force reallocation did take place in favour of a higher human capital content, as a consequence of product and process innovation, but not of management innovation. However, this evidence does not apply to the South, making the higher skill labour force of this region more exposed to territorial dislocation effects coming from international competition shocks. Indeed, over the 2000-2005 period 80,000 graduated people emigrated from the South to the Centre-North of the country (Mocetti and Porello 2010).

The paper is organized as follows. Section 2 describes the dataset, Section 3 introduces the econometric techniques we have followed to estimate the causal effect of innovation on the within-firm share of white collar workers. Section 4 and 5 respectively report the estimates for Italy and its macro-region evidence. Finally Section 6 concludes.

2. The dataset

The econometric exercise presented in the next sections has been carried out on a sample of Italian manufacturing firms elaborated by Unicredit. The survey contains a great variety of information and a prominent part is obtained through a questionnaire submitted every three years. In principle, the three-year information deals with the general characteristics of the firm, such as: ownership and control, group membership, labour force, investment activity, innovation, R&D, internationalization, commercial channels and competition. The survey contains about 5,000 Italian manufacturing firms with more than ten employees. Information is stratified according to firms' dimension, sector and geographical criteria. Although Unicredit releases the survey for ten editions (formerly known as Mediocredito Dataset and later as Capitalia Dataset), merging the different waves produces the loss of a high number of observations, about 80%. Another limitation of the dataset is due to the number of missing data that for many questions reaches a very high share of surveyed firms. A complete and detailed description of the results arising from descriptive analyses of the 2004-06 wave can be found on the Unicredit web site available at http://www.unicreditcorporate.it/eventi/eventi/2009/doc/02/rapporto.pdf.

We limit ourselves to report the descriptive stats for the variables actually included in the econometric estimates for which we have complete information. To our purpose, the relevant section of the dataset is the one devoted to innovation activity carried out by the firms in the 2004-06 period. In particular, innovations are distinguished in product, process and management innovation. The latter, in turn, consists in product-management innovation and process-management innovation.

By product/process innovation it is meant the introduction of a new product/process or a notably improved one, while by management innovation it is meant a managerial and/or organizational change somehow linked to product/process innovation. It follows that it is possible to have information on the firms that have carried out the different types of innovation by combining them in different ways.

Table II reports the number and the share of the innovating firms in the sample, for different definitions of innovation[1]. Shares are computed on the total sample span, 5,137 firms. As it is possible to see, in six cases out of nine the distribution of innovating firms with respect to non-innovating is strongly unbalanced in favour of the latter. In the remaining three cases – at least one innovation of any type, at least one product innovation and at least one process innovation - the share is around 50%, ranging from 42,65% to 62,76%. For this reason we will restrict our attention to these three definitions of innovation[2].

3. The econometric technique used to estimate the effect of innovation on labour force composition

The decision to innovate is subject to the self selection problem, being endogenous to the firm. It is reasonable to assume that firms with higher human capital are more inclined to innovate and, in turn, innovation is likely to induce higher human capital within the firm. To cope with the self selection problem a variety of econometric techniques have been developed in the literature. In order to single out the effect of innovations on labour force composition, measured as the share of white collar workers over total employment, we have chosen the Propensity Score Matching estimator. This choice has been motivated by the composition of the dataset. Alternative estimators are not suited for our case. The Difference in Difference estimator, DID, is applicable on panel data. Moreover, the DID estimator requires at least one observation for each firm in the pre-treatment period, which is not available. Further, instrumental variables does not allow to estimate the Average Treatment Effect, but only the

[1] In Table 2 only nine possible combinations of the definitions of innovation are reported. Actually, other four combinations are possible, that is: only product-management, only process-management, product innovation and process-management, process innovation and product-management. These last four have not been included in the Table because there are virtually no firms.

[2] A strong unbalance between treated and non-treated units in a propensity score matching increases the standard errors of the estimates, causing an over acceptance of the null of no significant effect.

Local Average Treatment Effect (Angrist and Pischke 2008, Angrist *et al*. 1996, Angrist 1990), provided one has a good instrument. Yet, the two steps Heckman estimator does not overcome the problem of finding a good instrument and also makes some additional distributional hypothesis, differently from the matching estimator (Heckman 1979 and 1978).

At its very essence, the matching estimator is an estimator apt to gauge the average treatment effect on the treated, ATT, comparing treated to "similar" non-treated units. The similarity is established according to a statistical criterion, as we will see in detail shortly. From a purely empirical point of view, the estimator is computed in two steps. The first one consists in a Logit estimate where the binary treatment variable, "innovation" in our case indicating the firms that have made innovations, is regressed on some covariates. From this estimate one retrieves the probability of innovating for each firm in the sample. This is the so called Propensity Score, or Pscore.

In the second step the data are stratified in blocks, or cells. Within each cell lie comparable innovators and non-innovators. The cells are built as Pscore intervals, such as: 0-0.1; 0.11-0.25; ...; -1. The treatment effect is computed within each cell and aggregated through a weighted mean.

Although Logit regressions are easy to run, not any specification suits the first step. In order to compare within each cell treated and non-treated units it is essential that the assignment to treatment is random with respect to the observables (Wooldridge 2002). That is, within each cell treated and non-treated units must not statistically differ in the value of the covariates. This principle is referred to as the balancing property and is the foundation of the "statistical similarity".

The balancing property can be formalized as follows: $D \perp X \mid p(X)$ where **D** stands for the dichotomous treatment variable identifying the treated units, **X** is a matrix of covariates and **p(X)** is the probability of being assigned to treatment, i.e. the Pscore. As a consequence, only the Logit estimates satisfying the balancing property can be taken to work out the Pscore. Accordingly, the next Section reports only the Logit estimates satisfying the balancing property, for each definition of innovation[3].

4. The Estimates

The second column of Table III reports the Logit estimates for the firms that have introduced at least one innovation of any type. The first step has not a behavioural interpretation, in the sense that all we are interested in is to find some significant covariates that help in predicting the probability of treatment, and at the same time fulfil the balancing property (Deheja and Wabba 2002). Nevertheless, it is worth discussing some relevant issues arising from the estimates. The probability to innovate is positively and significantly affected by: firm's dimension, measured as the (log) of total number of employees, the fact to be part of a consortium, investments in plants, machinery and equipments and exporting activity. The evidence of a positive effect of firm's dimension is in accordance with Blind and Jungmittag (2004), Bertschek (1995), Zimmermann (1987) for Germany, Bhattacharya and Bloch (2004) for Australia, Salomon and Shaver (2005) for Spain, Evangelista *et al*. (1997) for Italy and many others. Similarly, the positive contribution of exporting activity to the probability of innovating is in line with Blind and Jungmittag (2004) and Bhattacharya and Bloch (2004) for Germany, Salomon and Shaver (2005) for Spain, Bratti and Felice (2010), De Nardis and Ventura (2010) and Manesse *et al*. (2004) for Italy, among others. The positive relationship between consortium membership and innovation activity is not new in the economic literature both theoretical and empirical. In particular, the literature about industrial districts highlights the crucial role of external economies exploitable by the firms belonging to a network (Boix

[3] For instance, a variable indicating the share of retrained workers is omitted from the first step, although positive and significant, because it prevents the balancing property to be satisfied.

and Trullen, 2010, Robertson *et al*. 2009, Cainelli, De Liso 2005). Finally, the positive role of productive investment is in line with Sterlacchini (1998) who, on a different sample of Italian manufacturing firms, found that capital goods are an essential input of innovation activity.

We control for the influence of geography and sector specialization. As for geography we consider the four large regional partitions of the Italian economy, i.e. South, Centre, Northeast and Northwest and take the latter as reference group in our analysis. As for specialization we distinguish between Traditional and Non-Traditional industries. The breakdown between the two groups is based on the Pavitt's taxonomy, so that Non-Traditional activities involve Specialised Suppliers, Economies of Scale and Science Based industries. In our analysis we take the Non-Traditional sectors as reference group. Econometric testing shows that neither geography nor sector dummies are statistically significant. This evidence seems to point out that for a firm there is not an advantage in terms of probability to innovate by being located in the North, in the Centre or in the South; there is neither an advantage by being operating in a specific industry. Sectors and locations are not by themselves distinctive features of innovation capacity. This evidence holds true even when the regional dummies are interacted with the sector ones, as reported in the first three rows of the table. Diagnostic tests have also shown the absence of significant effects when the other variables included in the estimates are interacted with the regional dummies[4].

The third column of Table III reports the same econometric exercise on a different definition of innovation. In this case the firms are considered to be innovative if over the years 2004-06 have introduced at least one product innovation. The results are not qualitatively different from those reported in column 2 and just discussed.

Finally, the fourth and last column shows a significant negative sign for the firms operating in the traditional sector and located in the South. These firms are relatively disadvantaged. The marginal effect amounts to 12.26%, indicating that being located in the South and operating in the traditional sectors decreases the probability to introduce a process innovation by 12.26% with respect to other firms. At this point a clarification is in order. The reference group for comparison is given by the firms operating in the non-traditional sectors wherever they are and by the traditional firms located in the Northeast, the omitted group. But being the other two dummies not statistically significant, i.e. Centre and South, they do not show difference with respect to the comparison group. Therefore, one can conclude that the only disadvantaged firms are those located in the South and operating in the traditional sectors.

The estimates reported in the columns of Table III have been used to work out the propensity score for each definition of innovation.

Table IV reports the second step of the application of the Propensity Score Matching estimator, through which it is possible to estimate the ATT, namely the average effect of the innovation on the share of white collar workers, according to the different definitions of innovation.

For sake of completeness we report in the first column of Table IV all the four algorithms implementing the propensity score. The second column reports the number of treated and (in parentheses) non-treated units entering the experiment, for each algorithm. The third column finally reports the ATT at conventional levels of confidence and the standard errors in parenthesis.

At a first look, the estimates of both the ATTs and their standard errors seem stable across the different algorithms. An exception is given by the nearest neighbour algorithm, suffering from a remarkable loss of non-treated units, for each type of innovation.

[4] We cannot reject the hull hypothesis of equality of the estimated coefficients for the three macro-regions: Northwest, Centre and South when interacted with the following variables: "investments in plants, machineries and equipments" Chi2=1,89, P-value=0,389; "belongs to a consortium" Chi2=4,12, P-value=0,13; and finally for "exporters" Chi2=1,78, P-value=0,410.

Three characterizing results emerge from the table. First, introducing innovations causes the share of white collar workers to increase. Second, the different types of innovations lead to different outcomes. In particular, product innovation induces the highest effect, causing the outcome variable to increase by about 3-5%, according to the algorithm. Averaging over the algorithms the ATT of product innovation amounts to 4.1%. As far as the other two types of innovation are concerned we find an average ATT equal to 3.65% and 3.4% for process and for any type of innovation, respectively. Finally, differently from Piva et al. (2005), we find that management innovation hardly affects labour force composition. This conclusion can be deduced from the previous two points. Particularly, we have seen that going from product to process innovation the (average) ATT decreases from 4.1% to 3.65%. The ATT of any innovation (product, process and management innovations) is 3.4%, that is lower than former values Since increasing the information set one finds a lower effect than that computed for product and process innovation, it can be consistently concluded that the extra piece of information, i.e. management innovation, is responsible for the decrease in the ATT. Therefore, management innovation leaves the share of white collar workers unaltered or even decreases it. In principle, this conclusion might be directly testable by repeating the experiment using only those firms that have introduced management innovations. Unfortunately, in this case there is a strong unbalance between treated and non-treated units, as shown in Table II, preventing the result from being considered as reliable[5].

5. Regional Dimension of the effect of innovation on labour force composition

We saw from the logit estimation that the probability to innovate is uncorrelated with geography: other things being equal, a firm in the South has the same probability to innovate as a firm in the North. However this result doesn't say anything about possible geographical differences in the impact of innovation activity on labour force composition of innovating firms. To address this issue, the matching estimator has been applied on four subsamples composed of the firms located in the four Italian macro-regions, times the three types of innovation. Table V reports the distribution of the number and the share of innovating firms in the four macro-regions, for product innovation.

As can be seen from the table, at macro-region level the share of innovating firms is substantially unaltered with respect to that of the whole country. Indeed, for the macro-regions the share ranges from a minimum of 45.39% in the South to a maximum of 51.08% for the Centre, against a 49.04% at national level (see Table II). In spite of the stability of the innovators' share we find a sizable dispersion of the number of innovators across the macro-regions. Indeed, in the Northwest the number of innovating firms is almost four times as large as the number in the South.

The estimates show some positive and significant effect of product innovation on labour force composition for firms in the Northwest and the Northeast. However strength of evidence is quite different for these two macro-regions. The highest figures are recorded for the Northwest firms where the causal effect ranges from 5.6% to 8%, according to the algorithms. The figures in the range are always above the national figures (see Table IV). The estimates for the Northeast show that only one algorithm out of four gives rise to an ATT significantly different from zero, signalling a more uncertain impact of innovation. Eventually, for the Centre and the South there is not a significant effect. Because of the little number of observations in these last two subsamples the standard estimates have been bootstrapped, thus we can take the non significant result as reliable and not attributable to the number of observations.

Changing the definition of innovation. As for process innovation we confirm the results for the firms in the Northwest (strong and significant impact), Northeast (more

[5] The same econometric exercise has been repeated over the previous wave of the Unicredit Survey, 2001-2003. Very similar results have been found. Proof can be given to the interested reader upon request.

uncertain effect) and the South (null effect), while differences have been found for those located in the Centre where this kind of innovation proves effective in causing the share of white collar workers to increase(Table VIII). In the case of the broadest definition of innovation, including management besides product and process innovation, evidence of causal relationship is detected only for Northwest and Centre firms (Table X).

Summing up, the regional evidence can be summarized as follows. Taking the broadest definition of innovation it is possible to find a positive and significant effect on the share of white collar workers for firms of the Northwest and the Centre. Narrowing the definition to product innovation there are significant effects for firms in the Northwest and barely in the Northeast, but not in the Centre. It follows that process innovation causes the shift in statistical significance for the Centre[6]. A piece of explanation to reconcile this evidence may be related to firms characteristics, in terms of size and specialization, prevailing in the different areas. Significant effects of process innovation on labour composition are detected in regions where predominate firms that are large and specialized in scale-economies sectors, such as those in the Northwest and in some regions of the Centre. For North-western firms are also identifiable impacts on labour force composition induced by product innovation. In the case of Northeast, where are predominant small-sized firms specialized in sectors more exposed to competition of low cost producers of emerging countries, both product and process innovations seem to play a lesser role in changing labour force composition. In the case of these firms, low-cost foreign competition is mainly faced with vertical and horizontal product differentiation; both actions require investments in such intangible assets, as research, design, marketing and the likes; these are all skill-intensive activities, but they are also typically outsourced by a small manufacturing firm.

6. Conclusions

In this article we have analyzed the effect of innovation activity on labour force composition within the firm. The analysis has been carried out on a sample of Italian manufacturing firms investigating also the presence of territorial differences. In particular, the evidence points out that the probability of innovating is positively affected by firm's dimension, membership of a consortium, productive investments and exporting activity. These variables play a positive role for all the firms, for any sector and no matter where they are located. However, this regularity comes across an exception for the firms operating in the traditional sectors and located in the South. Controlling for the probability to innovate, the effect of innovation computed on the whole country seems to generate an increase in the share of white collar workers. Under this respect, product innovation is more effective than process innovation, while management innovation does not seem to positively affect labour composition. This evidence holds true for the Northwest and to a lesser extent for the Northeast. Process innovation proves instead effective both in the Northwest and the Centre. No innovation activity affects the share of white collar workers in the South, for any definition of innovation activity.

Such findings contribute to shed some light on the difficulty to retain high skill workers in the lagging regions of Italy, the so called brain-drain phenomenon. It doesn't seem to be only a problem of scarcity of innovating firms: other things being equal, a firm located in the South has the same probability to innovate as one in the North. Crucial differences emerge as far as the effects of such innovations are concerned: contrary to what happens for Centre-Northern firms, Southern ones are unable to increase the share of high skill workers.

[6] Repeating the regional analysis on the 2001-03 wave NE and S do not show significant differences for process innovation. Whereas, the remaining two regions register a neat increase of the average ATT. The NW increases from -1.4% to 6.4% and the C increases from -2.2% to 6.9%. Taking "any innovation" as reference, NW and C both increase from about zero to 6%. At the same time, NE and S show the opposite temporal dynamic, moving from about 2% in 2001-03 (2.85% NE and 1.95 for the S) to a non significant effect over 2004-06.

This may be due to differences in the kind and intensity of innovation adopted by firms in the Centre-North and in the South, differences that may be not detectable in the quite general partition of innovation activities available in the statistical dataset. Whatever the reason, such ineffectiveness of innovation efforts has not helped to stop the continuing migration of high-skilled workers towards the Northern and Central regions; a movement that has likely contributed to deepening duality in the Italian Economy. In order to keep human capital in the South increase of attraction of firms by itself may be not sufficient; also the effectiveness of innovation processes in increasing skill requirements of incumbent firms has to be substantially improved.

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Appendix

Table I. Descriptive statistics for some variables included in the Unicredit Database 2004-06 wave.

Variable	**number**	**Mean (s.d.)**
Firms operating in traditional sectors[7] (dummy variable)	1,267	0.31 (0.46)
Northwest (dummy variable)	1,267	0.38 (0.49)
Northeast (dummy variable)	1,267	0.32 (0.47)
Centre (dummy variable)	1,267	0.18 (0.38)
South (dummy variable)	1,267	0.13 (0.33)
Employees	1,267	138.51 (492.09)
Consortium membership (dummy variable)	1,267	0.03 (0.18)
Investments in plants equipments and machineries	1,267	0.75 (0.43)
Exporters (dummy variable)	1,267	0.62 (0.49)
Share of white collars	1,267	0.41 (0.26)

[7] The so called traditional sectors are composed of the following 2 digit Nace rev1.2 codes: food and beverages (15), textile (17), clothing (18), leather and leather products (19), manufacture of wood and wood products (20), furniture and other manufacturing industries (36).

Source: elaborations on Unicredit database

Table II. Number and share of the innovating firms per innovation type.

	Freq	%
At least 1 innovation of any type	3,224	62.76
Only product innovation	706	13.74
Only process innovation	396	7.71
Product and process innovation	1,257	24.47
At least 1 product innovation	2,519	49.04
At least 1 process innovation	2,191	42.65
Both management innovations	30	0.58
Product and product-management	118	2.30
Process and process-management	90	1.75

Source: elaborations on Unicredit database

Table III. Logit estimates of the probability to innovate.

	At least 1 innovation	At least 1 product innovation	At least 1 process innovation
Traditional sectors Northwest	0.078 (0.225)	0.194 (0.216)	-0.018 (0.223)
Traditional sectors South	-0.359 (0.277)	-0.132 (0.276)	-0.572* (0.298)
Traditional sectors Centre	0.346 (0.239)	0.317 (0.230)	0.239 (0.233)
(log) employees	0.428*** (0.052)	0.321*** (0.049)	0.365*** (0.051)
consortium membership	0.896** (0.376)	0.654** (0.332)	0.978*** (0.342)
Physical investment in plants, equipments and machineries	0.873*** (0.151)	0.571*** (0.156)	0.832*** (0.165)
Exporters	0.706*** (0.134)	0.576*** (0.135)	0.444*** (0.138)
Constant	-2.570*** (0.212)	-2.485*** (0.210)	-2.803*** (0.222)
Numb. Observations	1267	1267	1267

Standard errors in parenthesis, "***", "**" and "*" respectively denote 1%, 5% and 10% significance level.

Table IV. Effect of innovation on the share of white collar workers

	Treated (non-treated)	ATT
At least 1 innovation		
stratification	678 (589)	0.03* (0.018)

Kernel (Bootstrap)	678 (589)	0.035** (0.016)
Radious	678 (589)	0.025 (0.016)
Nearest Neighbor (random draw version)	678 (402)	0.046* (0.025)
At least 1 product innovation		
Stratification	510 (756)	0.05*** (0.015)
Kernel (Bootstrap)	510 (756)	0.048*** (0.016)
Radious	510 (756)	0.038** (0.015)
Nearest Neighbor (random draw version)	510 (470)	0.027 (0.019)
At least 1 process innovation		
Stratification	494 (773)	0.043*** (0.016)
Kernel (Bootstrap)	494 (773)	0.043*** (0.014)
Radious	494 (773)	0.032** (0.016)
Nearest Neighbor (random draw version)	494 (439)	0.028 (0.021)

Number of control units in parenthesis in the second column. SE in parenthesis in the third column. "***", "**" and "*" respectively denote 1%, 5% and 10% significance level. Where not possible to compute analytically the SEs they have been bootstrapped with 200 replications as suggested by Moonye, Duval (1993).

Table V. Number and share of innovating firms per macro-region (product innovation)

	Freq	%
Northwest	1,076	48.84
Northeast	741	49.66
Centre	426	51.08
South	276	45.39

Source: elaborations on Unicredit database

Table VI. Effect of innovation on the share of white collar workers in the Italian macro-regions (product innovation)

	Treated (non-treated)	ATT
Northwest		
Stratification	189 (289)	0.079*** (0.023)
Kernel (Bootstrap)	189 (289)	0.075*** (0.024)
Radious	189 (289)	0.056** (0.026)
Nearest Neighbor (random draw version)	189 (121)	0.076** (0.03)
Northeast		
Stratification	160 (242)	0.039 (0.026)
Kernel (Bootstrap)	160 (242)	0.045* (0.024)
Radious	160 (242)	0.04 (0.026)
Nearest Neighbor (random draw version)	160 (114)	0.038 (0.035)
Centre		
Stratification (Bootstrap)	98 (116)	0.036 (0.034)
Kernel (Bootstrap)	101 (113)	0.035 (0.032)
Radious (Bootstrap)	98 (113)	0.3 (0.036)
Nearest Neighbor (random draw version, bootstrap)	101 (58)	0.06 (0.04)
South		
Stratification (Bootstrap)	60 (100)	-0.037 (0.071)
Kernel (Bootstrap)	60 (100)	-0.028 (0.055)
Radious (Bootstrap)	60 (100)	-0.001 (0.047)
Nearest Neighbor (random draw version, bootstrap)	60 (100)	0.009 (0.083)

Number of control units in parenthesis in the second column. SE in parenthesis in the third column. "***", "**" and "*" respectively denote 1%, 5% and 10% significance level. Where not possible to compute analytically the SEs they have been bootstrapped with 200 replications as suggested by Moonye, Duval (1993).

Table VII. Number and share of innovating firms per macro-region

(process innovation)

	Freq	%
Northwest	937	42,53
Northeast	620	41,55
Centre	391	46,88
South	243	39,97

Source: elaborations on Unicredit database

Table VIII. Effect of innovation on the share of white collar workers in the Italian macro-regions
(process innovation)

	Treated (non-treated)	ATT
Northwest		
stratification	182 (290)	0.061** (0.025)
Kernel (Bootstrap)	184 (288)	0.065*** (0.025)
Radious	183 (288)	0.045* (0.026)
Nearest Neighbor (random draw version)	151 (104)	0.058* (0.034)
Northeast		
Stratification	150 (252)	0.017 (0.03)
Kernel (Bootstrap)	151 (251)	0.029 (0.026)
Radious	151 (251)	0.022(0.027)
Nearest Neighbor (random draw version)	151 (104)	0.058* (0.034)
Centre		
Stratification (Bootstrap)	89 (113)	0.071** (0.034)
Kernel (Bootstrap)	89 (113)	0.069** (0.032)
Radious (Bootstrap)	89 (113)	0.066** (0.033)
Nearest Neighbor (random draw version, bootstrap)	89 (113)	0.096** (0.045)
South		
Stratification (Bootstrap)	60 (99)	-0.006 (0.59)
Kernel (Bootstrap)	60 (99)	0.013 (0.051)
Radious (Bootstrap)	60 (99)	0.018 (0.047)
Nearest Neighbor (random draw version, bootstrap)	60 (41)	0.006 (0.057)

Number of control units in parenthesis in the second column. SE in parenthesis in the third column. "***",

"**" and "*" respectively denote 1%, 5% and 10% significance level. Where not possible to compute analytically the SEs they have been bootstrapped with 200 replications as suggested by Moonye, Duval (1993).

Table IX. Number and share of innovating firms per macro-region (any innovation)

	Freq	%
Northwest	1,379	62.60
Northeast	935	62.67
Centre	560	67.15
South	350	57.57

Source: elaborations on Unicredit database

Table X. Effect of innovation on the share of white collar workers in the Italian macro-regions (any innovation)

	Treated (non-treated)	ATT
Northwest		
stratification	249 (229)	0.072*** (0.023)
Kernel (Bootstrap)	249 (229)	0.077*** (0.024)
Radious	249 (229)	0.053* (0.027)
Nearest Neighbor (random draw version)	249 (116)	0.06** (0.026)
Northeast		
Stratification	218 (184)	0.009 (0.033)
Kernel (Bootstrap)	218 (184)	0.009 (0.033)
Radious	218 (184)	0.005 (0.027)
Nearest Neighbor (random draw version)	218 (102)	0.007 (0.04)
Centre		
Stratification (Bootstrap)	121 (83)	0.059* (0.035)
Kernel (Bootstrap)	121 (83)	0.06** (0.03)
Radious (Bootstrap)	121 (83)	0.055* (0.029)
Nearest Neighbor (random draw version, bootstrap)	121 (55)	0.094** (0.037)
South		
Stratification (Bootstrap)	71 (88)	-0.015 (0.051)
Kernel (Bootstrap)	80 (79)	-0.055 (0.067)
Radious (Bootstrap)	75 (79)	0.004 (0.047)

Nearest Neighbor (random draw version, bootstrap)	80 (41)	-0.12 (0.113)

Number of control units in parenthesis in the second column. SE in parenthesis in the third column. "***", "**" and "*" respectively denote 1%, 5% and 10% significance level. Where not possible to compute analytically the SEs they have been bootstrapped with 200 replications as suggested by Moonye, Duval (1993).