Organizational Innovations and Labor Productivity in a Panel of Italian Manufacturing Firms.

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Abstract

We study determinants of the probability of introducing an organizational innovation using three large cross sections of Italian manufacturing firms in the period 1995-2003. We analyze the effect and complementarity of other types of investments, like ICT, R&D, human and physical capital and the adoption of product or process innovations. Furthermore, we estimate the effect of introducing organizational innovations and indirectly technical innovations on the growth rate of labor productivity for the unbalanced panel of firms. Disembodied technological change is well represented by OIs, while product

innovations seem to have an effect on the efficiency of capital inputs only (capital stock-embodied technical change). Process innovations do not have a statistical impact as an indirect input-efficiency driving force, in our data.

1 Introduction

The organizational activity inside a firm and its innovations has been an interesting yet not widely analyzed topic of discussion, among empirical economists and those who are looking for relevant factors to explain the long-run declining total factor or labor productivity, especially in Italy. As Francesco Daveri (2006) explains in his book, referring also to his own previous work i.e. [5, Daveri and Jona-Lasinio, 2005], per capita GDP in Italy has seen a continuous decline since the 1970s, and the main cause of this decline in the 1995-2005 period is mainly attributable to very low growth rates of labor productivity (+0.5% per year in 1995-2004, with respect to +3.5% per year in 1993-95[1]) measured as GDP per hours worked. This is a negative fact if compared to the rest of European countries, which altogether had a productivity of labor growing at 1.5% in the same years, and to the US productivity which grew at 2.1% (+4.4% only in the manufacturing sector). If in the US the time after 1995 has been named "The New Economy" era, after a resurgence of productivity especially in the manufacturing sector, this was due basically to new investments into software and hardware and other new technologies, as well as to the more and more diffused practice of letting non-managerial employees to be involved into problem solving [2, Black and Lynch, 2004]. Interestingly, the same time period Italy saw an

[1] [4, Daveri, 2006] cites OECD data.

increase in the hours worked by each employee, therefore not working less than her/his European or American colleagues, but less productively. This problem has not only an economic impact in prospect (reduced per capita income, relative reduction of the quality of life, etc.) it has effects also on decreasing the competitiveness of Italian firms. Mainly, low productivity rates have been thought of as the consequence of changes in the labor market institutions. New types of flexible contracts, especially for the young, introduced in the 1990s in Italy, have added to the workforce less experienced, unskilled young people, and higher hiring rates in those sectors which are typically characterized by low productivity (as Services and Constructions). Few and late investments in communication and information technologies are also considered to matter at reducing labor productivity [1, van Ark et al., 2003]. The empirical literature on this issue gives controversial results, though. At the individual level, being able to use a computer has not a significant higher impact on productivity and wages than being able to use more traditional work tools. Possessing complementary computer skills such as problem solving abilities or communication and networking abilities makes the difference [8, Di Pietro, 2006]. At more aggregate level, productivity is higher in businesses with more-educated workers or greater computer usage by nonmanagerial employees [3, Black and Lynch, 2001]. However, [6, Daveri, 2004] shows that European non-ICT intensive and ICT intensive sectors have both suffered from productivity slowdown.

In this paper, we argue that labor productivity might be affected by the entire firm organization. Business organization shapes work practices and as such might have an relevant impact on productivity of labor at the individual and micro level. By modifying few practices for employees (for example, giving them more formal training or allowing them to unite in project teams) or ways of doing business, in few words by introducing organizational innovations, firms might obtain huge advantages in terms of improved productivity. As Sanidas (2005) discusses extensively, we distinguish technical (direct) innovations that result in the form of "embodied technological progress", i.e. new technology embodied in the capital goods, from organizational innovations that affect technology "disembodied in such forms as industrial property rights, unpatented know-how, management and organization and design and operating instructions for production systems" (Sanidas, 2005).

On the other hand, organizational innovations are endogenous decisions inside a firm. [9, Lynch, 2007] analyzes empirically the issue of the determinants of the adoption and diffusion of new work practices (like workforce receiving formal training, team groups, discussion meetings on a regular basis, job rotation, and incentive pays). She uses two cross sections of US manufacturing and non-manufacturing establishments during the 1990s. She finds that employers with more *external focus* (being part of a multi-establishment firm, exporting their main product, and benchmarking) are more likely to invest into organizational innovations. Investments into R&D activities, more skilled workforce, physical capital and ICTs are complementary to organizational innovations. High past operating profits and being young are also important determinants for inducing new work practices.

Our paper studies empirically the adoption of organizational innovations by Italian firms in the years between 1995 and 2003. Furthermore, we are interested in the correlation between the organizational activity and innovations with labor productivity improvements, by regressing the annual growth rate of firm's labor productivity on the introduction of organizational innovations related to production processes or new products. In other terms, we test the hypotheses of embodied and disembodied technological change using a production function-growth accounting approach.

The paper is shaped as follows: Section 2 describes the data used in the empirical analysis, the construction of the panel, the distinction between technical and organizational innovations within the data, and discusses the variables of interest. Section 3 discusses how to incorporate disembodied and embodied technological change into the production function. Section 4 illustrates the results of the logit regressions and the productivity regressions. Section 5 draws the conclusions.

2 Data description and discussion

We use the data from the VII, VIII and IX *Indagine sulle Imprese Manifatturiere* by Capitalia (once known as Mediocredito Centrale), which are the only Italian firm surveys containing information on the introduction of organizational innovations in the firms, as far as our knowledge goes. These surveys were conducted in 1998, 2001 and 2004 respectively, through questionnaires handed to a representative sample of manufacturing firms[2] within the national borders, and supplemented with standard balance-sheet data. Questionnaires collect information over the previous three years. As far as the introduction of innovations is concerned, firms were generally asked to say whether they had introduced any innovation (including product, process, organizational) in the previous three-years period. In particular, in this paper we use the answers to the question regarding the introduction of technical-organizational innovations related to products and the question regarding the introduction of technical-organizational innovations related to production process, which we call *destination-type organizational innovations.* An

[2]The most recent survey run in 2004 include also non-manufacturing firms in the Construction and Service sectors.

example of organizational innovation related to product might be involving employers in finding a solution to defective products. An example of organizational innovation related to process might refer to rearranging jobs or re-engineering. Unfortunately, the questionnaires handed out do not go more deeply as to ask respondents to specify types of re-arrangements or new organization-related issues. They just had to say whether the firm introduced such an innovation or not. Each survey contains about 4.500 manufacturing firms, and we make use of the three (cleaned) cross sections separately when analyzing the probability of introducing one type of innovation.

2.1 Organizational and Technical Innovations

Table 2 shows the mean value of the product-type and process-type organizational innovations for each survey (OI_pd and OI_pc). On average, across the surveys 15.6%-20% of firms introduced organizational innovations related to new products, with an increasing path over time. 15%-23% of firms introduced OIs related to production process, with a declining path over time. In our panel, on average more firms introduced OIs related to process than products (17.8% versus 15.5%). Table 2 shows the average number of innovating firms also conditional to size (large firms only), R&D-activity and High-Tech firms. The last four rows refer to conditioning on having introduced another type of OI or whether the firm has introduced a technical product or process innovation. Large firms employ more than 250 workers. R&D-active firms are those firms which invested into research and development activities at least once along the survey period. High-tech firms are those whose main production activity is in the following sectors: Chemistry, Plastic and Rubber, Office and Precision machinery, Electrical machinery.

We also try to analyze the probability for the panel, which is quietly reduced in dimension, but allows to consider past behavior in terms of innovating activity. The panel component of the three waves is made up by firms for which we have at least two consecutive observations (i.e. firms that appear in two or three consecutive waves). We obtain a reduced sample of 1.883 firms. Most of the firms within the panel (929, corresponding to 49.34%) come from the 8th survey and to a smaller extent from the other surveys (24.53% from the 7th and 26.13% from the 9th). Almost three-quarters of the firms (73.87%) appear only in two waves, while only 26,13% appearing in all the three waves.

The following descriptive tables show how the decision of introducing OIs does not come directly after or before the introduction of a technical innovation. In Table 3 we see that about 35% to 43% of the firms across the surveys when introducing a new product decided to introduce an OI related to product, too (34% to 46% for process related OIs). Table 4 viceversa, shows that when introducing OIs related to product the probability of introducing a new product is extremely high (85%-90%), while the probability is reduced for firms introducing OIs related to process and new production processes (53%-92%). Firms introducing OIs related to process have a substantial probability of introducing also TIs related to product (11%-49%).

2.2 Factors potentially affecting firms' decision to implement OIs

As regards the determinants of the probability of introducing organizational innovations, size can be important because large firms are more likely to need frequent restructuring of their more complex organization than small firms. Size is shown in the literature to have persistence effects, when firms introduce process or product innovations directly. Large firm innovations effects on productivity last at least twice as much as small firm innovations [11, Rochina-Barrachina et al., 2008].

Present and future profitability opportunities might require re-organizing, at least when there are prospects of merger and acquisitions. Per worker operating profits and per worker cashflow (average in the three years) are the proxy used, respectively.

Being part of a group may affect organizational decisions because of extended practices by parent firms or other members of the group. Exporting all or part of the production means that the firm might be under competitive pressure internationally. Rearranging work practices could result in costs reduction or higher product quality.

Human capital accumulation represents the skill capacity of a firm, the basic factor for a firm to be competitive, innovative and productive. We measure this by a series of available information on the skill level of the workforce: the fraction of R&D workers on the total, the level of education, measured as the fraction of employees with a junior-high school degree, a high-school degree and a university degree. We have this information only for the last year of observation in each survey period. The fraction of blue versus white collars represents the type of occupation and qualification of the workforce.

Investment in new technology, like software and hardware or communication, can be complementary to innovating the organization of the firm. The idea that ICT has given rise to improved productivity at the individual, firm or more aggregate level is still a matter of controversy in the literature. Much of the literature has not found a direct effect of being able to use a computer in order to be more productive or having a higher salary, ceteris paribus. ICT investment has not a direct effect on firm's productivity either. That is why considering it as complementary to other types of innovation activity, it could have an indirect effect on labor productivity too. Being R&D active could have some degree of complementarity in the sense that R&D investment is found to be positively correlated to the introduction of direct process innovation, and, by interacting with innovative physical investment, it has an effect on the probability of introducing product innovations too [10, Parisi et al., 2006]. If the firm introducing a direct innovation has restructured the organization somehow, than we can check for this effect in our regressions.

We also check for a possible correlation between the introduction of direct production process innovation or a product innovation with the need of organizational innovations.

Finally we control for other firm characteristics like age, sector and geographical area dummies. [9, Lynch, 2007] in particular suggests that younger firms are the most dynamics in terms of innovation activity. Particularly interesting for Italy is to analyze the effect of being in sectors named under the label "Made in Italy", which includes the traditional Italian exports, like Machinery, Clothes, Textile and Food products.

The average values for each variable and each cross section are reported in Appendix A, Table 1.

Table 2 shows the percentage values of firms introducing a destination-type organizational innovation also conditioning on the set of firms with particular characteristics. Firms introducing a product-related organizational innovation vary between 12% to 20% according to the time period. This range goes up to 18%-26% if we look at large firms only (with more than 250 workers). R&D firms introduce product-related organizational changes in the percentage range 21%-34%. Firms defined as High-Tech (HT) vary in the 14%-25% range. If the firm has introduced also a process-related organizational innovation the average span is larger, 6%-37%. At last, when the firms have introduced direct product or process innovations at the same time of organizational changes, new organizational methods related to product range between 15% and 31%. On the other side, there are 15%-23% firms introducing a process-related organizational innovation according to the period considered, which therefore appears to be slightly more common. This range goes up to 16%-37% if we look at large firms only. R&D firms introduce process-related organizational changes in the percentage range 16%-35%. Firms defined in HT sectors vary in the 13%-24% range. This is evidence that firms engaged into R&D activity or firms in the high-technology sectors introduce with the same frequency either organizational innovations related to process or related to product. If the firm has introduced also a product-related organizational innovation the average span is even larger, 9%-73%. At last, when the firms have introduced direct product or process innovations at the same time, new organizational methods related to process range between 20% and 29%. Interesting to notice, almost one out of three firms needs to introduce organizational changes when they want to introduce new products or process innovations.

3 Embodied and disembodied technological change into the production function

We use a production function approach to test whether organizational innovations have a different impact on labor productivity with respect to technical direct product or process innovations. Assume a Cobb-Douglas production function of two inputs, Labor and Capital stock. The production is affected by a technology term which represents the disembodied technology not affecting the single-input efficiency, while labor and capital are affected by the so-called embodied technological change, which improve the efficiency of both inputs (they are measured in efficiency-units by so doing).

$$Y_{it} = A_{it}(Z_{it}K_{it})^{\alpha}(E_{it}L_{it})^{\beta} \tag{1}$$

where i refers to firm and t to time of observation. Real production Y_{it} depends on the capital stock accumulated and the labor input until the beginning of year t. Disembodied technology is such that progress depends on the introduction of organizational innovations, i.e.

$$\frac{\dot{A}_{it}}{A_{it}} = e^{\delta OI_{it}} \tag{2}$$

when no innovation is introduced, the level of the technology remains constant, otherwise it jumps up to a new upper level. Capital stock is measured in efficiency units in the sense that we take into account the embodied technology in capital goods (see Parisi et al., 2006). When a technical innovation is introduced (for example a process innovation), mostly embodied in new capital investments, then the efficiency variable can be written as

$$Z_{it} = e^{\gamma_1 TI_{it}} \tag{3}$$

Where TI_{it} are technical innovations like product or process innovations. These innovations might also induce an improvement in the efficiency of labor:

$$E_{it} = e^{\gamma_2 TI_{it}} \tag{4}$$

when there is no technical innovation, then capital or labor remain at their current non-quality adjusted level. In a more general sense, OIs might induce an improvement in the labor quality too, by producing better working practices, as discussed in the Introduction above. For this reason, we are going to measure efficiency labor also with the alternative term:

$$E_{it} = e^{\gamma_2 TI_{it} + \gamma_3 OI_{it}} \tag{5}$$

By substituting all these terms into the production function, taking logs and expressing the function in intensive form, we obtain a definition of labor productivity:

$$\ln \frac{Y_{it}}{L_{it}} = \ln A_{it} + \alpha \ln \frac{K_{it}}{L_{it}} + \beta \ln L_{it} + \alpha \ln Z_{it} + \beta \ln E_{it} \tag{6}$$

where we test the assumption of CRS with the data. This equation allows to test the effect of the various innovations on the level of labor productivity. Alternatively, and maybe more realistically, we are interested in the growth rate of labor productivity, and we will use the alternative expression to test the effect of the different types of innovations on the growth of labor productivity:

$$\Delta \ln \frac{Y_{it}}{L_{it}} = \Delta \ln A_{it} + \alpha \Delta \ln \frac{K_{it}}{L_{it}} + \beta \Delta \ln L_{it} + \alpha \Delta \ln Z_{it} + \beta \Delta \ln E_{it} \tag{7}$$

where Δ is the first-difference operator. We assume that innovations have an effect on the growth rates of the efficiency variables defined above:

$$\Delta \ln Z_{it} = \gamma_1 TI_{it} \tag{8}$$

$$\Delta \ln E_{it} = \gamma_2 TI_{it} + \gamma_3 OI_{it} \tag{9}$$

The parameters of interest in equation (7) could suffer from non identifiability, unless we restrict our attention to particular types of innovations. When we assume that the level of disembodied technology is affected by OI_pd, then we need to assume that only OI_pc affects the efficiency of labor, in order to identify the parameters δ and γ_3 (and viceversa). In the same spirit, when TI_pd affect the efficiency of capital goods, then TI_pc may affect the efficiency of labor input, in order to identify γ_1 and γ_2 and viceversa. Our exercise is to test for the following (nested) model specifications:

1. Model: disembodied technical change derived from process OIs, $\delta \neq 0$
2. Model: disembodied technical change derived from product OIs, $\delta \neq 0$
3. Model: disembodied t.c. derived from process OIs plus embodied technical change for capital input only, $\delta \neq 0$, $\gamma_1 \neq 0$
4. Model: disembodied t.c. derived from product OIs plus embodied technical change for capital input only, $\delta \neq 0$, $\gamma_1 \neq 0$
5. Model: disembodied t.c. derived from process OIs plus embodied technical change for capital input and labor input, $\delta \neq 0, \gamma_1 \neq 0, \gamma_2 \neq 0$
6. Model: disembodied t.c. derived from product OIs plus embodied technical change for capital input and labor input, $\delta \neq 0, \gamma_1 \neq 0, \gamma_2 \neq 0$

   According to the model specification, the parameter δ could be referring to process OIs or product OIs, the parameters γ_1 and γ_2 refer to process innovations or product innovations (TIs). For the moment, we assume $\gamma_3 = 0$.

4 Empirical Results

4.1 Estimated impact of the determinants of OIs

We study the probability of introducing a destination-type organizational innovation (OI) as a logit model on several firms characteristics. The dependent variable in Table 9 is "organizational innovation related to product", and in Table 10 it is "organizational innovation related to production process". Columns 2-4 refer to a different survey period (1995-1997, 1998-2000, 2001-2003). Observed firms characteristics affecting this probability, as discussed previously, are the following: size, the average operating profit per worker, the average cashflow per worker (proxy for future profitable opportunities), whether the firm belongs to a group, whether it has exported part or all its main product, the number of R&D workers relative to total occupation, the fraction of employers with a junior-high school degree, high-school degree and university degree in the last year of observation, the fraction of blue collar workers and white collar workers in the total, whether it has invested into ICT technology in the survey period, whether it has invested into R&D activity, the fraction of employers who received training in the past three years and other firm characteristics like age, sector and geographical area dummies. In particular, we emphasize the importance of being in the traditional *Made in Italy* sectors which, more than others, would need restructuring and re-organizing work practices in order to remain competitive in the international markets.

In Table 9 we show the results of three different logit regressions, one for each period. The dependent variable is a (0,1) dummy indicating whether during the three years the firms have introduced an OI related to product. For the VII and IX survey, size, measured as the log of sales, is positive and significant at 1% level. Neither per worker operating profits or cashflow are statistically significant, meaning that present and future opportunities are not so important at determining this kind of innovations for Italian firms. It appears that being part of a group has either zero impact or slightly negative impact, while exporting the main product is, quiet interestingly, not important at all. In the 1998-00 period, the larger the fraction of R&D workers, the higher the probability of introducing a product-related organizational innovation. This is particularly relevant in the 2001-2003 period. In the 1998-00 period it appears to be slightly significant and positive the percentage of junior-high educated workers (with respect to the missing level of education, that is no education). No other level of education has a statistically significant estimate (% High school education is predicting the probability of not introducing the innovation perfectly, and therefore it is excluded from the variables).In the 1995-97 period the fraction of blue collars and white collars have a positive significant impact (with respect to the missing category: directors). They appear to be non significant in the rest of the years. For the product-related kind of innovation, it is very important to be R&D active all over the years. The R&D coefficients are significant at 1% level. Investing in Information and Communication Technologies (ICT) is positively correlated to the probability. The same is true when the firm has a larger fraction of employees and workers receiving formal training. Age doesn't count. As far as *Made in Italy* goes, Clothes/Textiles and Machinery sectors appear to have been engaged into product-type organizational changes only in the 1995-97 period. Machinery is negatively correlated with this probability in the subsequent three years.

In Table 10 we show the results of the logit regressions, by survey, when the dependent variable is the dummy: process-related organizational innovation. Size has no effect apart from a small positive effect in 2001-03. In the same years, operating profits per worker have a negative impact but cash-flow has a positive one. Process-related changes might have to do with future expectations of profitability. Now being part of a group appears to be important, especially in the VII and IX survey. The export dummy is still puzzling in the sense that it has a positive significant impact in 1995-1997 and then a negative significant impact in the next period. Having R&D workers do not seem to be relevant, while education is negatively related to the probability of introducing a process related change in 2001-03 (with respect to no education). As before, the fraction of manual workers and the fraction of white collars with respect to directors have a positive impact only in the first survey period. Being R&D active or investing in ICT is positively significant for the 1995-97 and 1998-2000 period, and non significant in the latest period. Formal training is positively related to the probability in the 1995-97 and the 2001-03 periods only. Again, age doesn't count for Italian firms innovation activity. Finally, it seems that the traditional Italian sectors of production did not go through organizational restyling directed to production process.

When regressing logits for the balanced panel, we are able to use past values of operating profits per worker, past innovation activity like average past R&D investments, average past physical investments, previous innovations introduction, including previous organizational innovations, to check for persistence. Table 2 in Column 3 summarizes the percentage of firms introducing organizational innovations in the panel of firms. These values confirm that large firms, R&D firms and HT firms are those more commonly innovating their organizations. This part of the research is still work in progress, though.

4.2 Estimated impact of OIs and TIs on labor productivity

The objective of the econometric exercise in this subsection is to select among different hypotheses on the impact of OIs and TIs on labor productivity growth. As a second objective, we want to select the most appropriate among specifications using econometric techniques and tests.[3] We estimates six models with four different estimation methods: simple OLS, Instrumental variables estimator (IV), Between estimator (BE) and IV on BE-converted data (IVBE). The first one is a benchmark approximate method, not necessarily consistent or efficient. IV takes care of potential endogeneity of specific explicative variables (i.e. the per capita capital stock and the introduction of organizational innovations). Instruments are selected according to weak exogeneity tests on OLS and the statistically significative coefficients in the logit regressions of subsection 4.1 and Tables 10 and 9. In particular, we use the following lagged variables for the growth rate of per capita capital stock: lagged Production in levels lnY_{it-2}, lagged capital stock in levels $\ln K_{it-2}$, lagged number of non-R&D workers in levels $\ln(\text{non-R\&D-workers})_{it-2}$. The instruments used for OIs related to process are: cash flow per worker, operating profits per worker, export dummy, R&D dummy, %investment in ICT, % trained workers. The variable OI related to product is instrumented by group dummy, export dummy, % workers in R&D activity, Investment in ICT dummy, % trained workers. These characteristics appear to have some meaning in the cross-section regressions of the separate waves, as discussed

[3]We use Hausman specification test to choose among alternative nested models. Unfortunately, this test is not particularly sensitive to the number of explicative variables included, when this is high, like our case, in which we control for areas, size and secotral dummies. It turns out that just adding one variable does not move the value of the test much.

above. BE estimator controls for potential time effects which would remain even after differenciating equation (6). Given that these are survey data and the regressions are performed on the unbalanced panel, it is plausible to assume that at least "survey" effects do remain. This possibility could be excluded by taking long-run growth rates of the labor productivity and the capital stock (differentiating per capita variables along the surveys time span and not just along the yearly dimension). This other exercise would fall in the robustness check.

Finally, even after converting the data with the between-group BE estimator, we need to instruments the capital stock and the OIs anyway (IVBE). Table 11 in the first panel compares estimates of Model 1 hypothesis with the four methods. It turns out that IV methods are preferred to the other two, according to Hausman specification tests. Moreover, weak exogeneity is rejected for the capital stock in OLS regression, while OI_pc does pass the test. If we believe to the logit specifications, then we are inclined to conclude that OI-pc has quite an impact on labor productivity growth, its (semi-)elasticity being equal to 0.42 (significant at the 10% level). In Model 2 we represent the growth in technology through organizational innovations related to product. The IVBE method can definitely be considered the best according to our criteria. This mean that OI_pd has a significant (semi-)elasticity equal to 0.15 (see Table 12). Disembodied technical change might show up in the form of both types of OIs.

Model 3 encompasses Model 1 by relating OI_pc to disembodied technical change, while assuming that technical innovations like new products might induce more efficient capital goods.[4] Although Hausman tests do not suggest

[4]We need to consider TI_pd in Model 3 to represent technical progress embodied in capital goods to reduce the problem of correlation in variables. Notice, however that the R^2 in Table 14 are low enough to avoid the presence of serious collinearity in the explicatives. See also the correlations in Tables

that Model 3 is somehow better than Model 1, still we find interesting results. The coefficient of OI_pc is 0.27 (lower than in Model 1 but still significant) in the IVBE column, and 0.31 in IV regression in column 2. Even TI related to product is statistically significant here (its coefficient being 0.075). Even more interesting, the estimate for γ_1 parameter, which measures the impact of TI_pd on capital goods efficiency. Its value is 0.55, statistically significant at 10% level.

Model 4 tests for the upside down hypothesis: disembodied technology is affected by OIs related to product, while capital goods efficiency is affected by TI related to process. Even here Hausman tests do not give precise indication on wether Model 4 is better than Model 2. Anyway, only IVBE shows a statistically significant coefficient for OI_pd, comparable in magnitude to that of Model 2. There is no statistically significant impact of TI_pc on capital goods efficiency (and therefore on labor productivity).

Model 5 encompasses Model 1 and Model 3 hypotheses. Hausman tests do not seem to prefer any of the methods to their equivalent in Models 1 or 3. In any case the IV and IVBE columns show interesting results. The impact of OI_pc remains the same as in Model 1 (0.47 in IV and 0.43 in IVBE). TI_pd has a significant semi-elasticity equal to 0.53, and it is assumed that is improves capital efficiency. This value, indeed, is entirely passed through the share α, given that the parameter estimate for γ_1 is statistically irrelevant. TI_pc is assumed to be the measure of labor efficiency. The coefficient is significantly different from zero, but it is negative both for IV and IVBE. Correspondingly, the estimate of γ_2 is negative too. It appears that TI_pc and TI_pd have a slight substitutability effect with each other.

Model 6 considers OIs related to product as the main technology driving

3 and 4.

force, but it gives no evidence in favor of this assumption. TI_pd now is the capital efficiency measure, while TI_pc is taken to improve labor efficiency. Hausman tests indicate that IVBE is to be preferred to its equivalent in Models 2 and 4, while BE is to be somehow preferred to its equivalent in Model 4 (but not in Model 2). There is no evidence in favor of both assumptions that indirect technical innovations are efficiency drivers.

5 Conclusions

We study determinants of the probability of introducing an organizational innovation using three large cross sections of Italian manufacturing firms in the period 1995-2003. We analyze the effect and complementarity of other types of investments, like ICT, R&D, human and physical capital and the adoption of product or process innovations. Having external focus is relevant only for process-related changes and if it regards being part of a group. Exporting the products abroad has a puzzling effect on the probability of introducing organizational changes. R&D activity is positively related to the probability, and the fraction of R&D workers is important for the introduction of product-related changes. ICT investments are strictly positively correlated to both types of innovations. Having more educated workers do not imply higher probabilities of re-organizing. Some positive sign is given by occupational types, either blue or white collar, with respect to directors and managers, and having formally trained employees is positively related to innovations (actually, training is one form of organizational innovation). Younger firms do not introduce more innovations than older firms. Furthermore, we discuss the effect of introducing organizational innovations and technical innovations on the growth rate of labor productivity at the firm level. The empirical estimates of the productivity regressions are still work in progress.

Since the objective of organizational innovations is mainly re-structuring work practices, it is quite curious that for Italian firms, workers related characteristics basically do not matter in order to introduce organizational innovations.

The second part of our paper focuses on the estimation of the impact of OIs and (indirect) technical innovations on the (short-run) growth rate of labor productivity. From the estimates it turns out that OIs related to process and product have quite a relevant impact on labor productivity growth, in the form of (direct) disembodied technological progress. Direct innovations, such as product innovations, appear to have a positive impact in driving the efficiency of capital goods. Process and product innovations, if used as indirect factors influencing labor productivity through improving the efficiency of the inputs, appear to have a certain degree of substitutability.

Our next research effort will be related to the robustness check of these findings, in various directions. We will replay the econometric exercise by 1) selecting only firms with actual observations in all three survey periods (balanced panel, reduced in dimension); 2) adding R&D intensity in the production function; 3) estimating the long-run growth rate of labor productivity on OIs and TIs as before, therefore controlling for the presence of "survey" effects; 4) at last, we reformulate the hypotheses in Model 1 to 6 by estimating equation (6) in levels, instead of growth rates.

A The independent variables of the logit regressions

Sales are expressed in thousands of euros, in logs. Operating profits and cashflow are expressed in thousands of €, per worker, and can take negative values. For dummy variables like belonging to a group, exporting its main product, doing R&D activity, invested into ICT, introducing a direct product or process innovation, and sectors dummies we show the percentage number of firms in each survey period. % R&D workers is the percentage number of R&D workers over total workers calculated as an average over the survey period. % Junior high, % High school, % University are the percentage of workers with a junior high school degree, a high school degree and a university degree, respectively, in year 2003. % Blue collar and % White collar are the percentage number of manual workers and employees, respectively, over total workers, taken on average over the survey period. The occupation missing in the regressions is the average percentage of directors. % formal training is the average percentage number of workers who received formal training paid by the firm (averaged over the three-year period). Age is measured as years of incorporation at the last year of observation of the survey.

Table 1: A. Mean percentage values of the independent variables by survey.

	1995-97	1998-00	2001-03
		Size	
ln(Sales)	9.44	9.24	9.29
		Profitability	
Operating Profits p.w.	12.55	7.20	8.95
Cashflow p.w.	26.92	14.03	17.01
		External activity	
Group	24.92	22.11	32.41
Export	71.48	70.20	74.94
		Skills endowment	
% R&D workers	1.20	7.40	3.58
% Junior-high	57.90	64.15	55.85
% High-school	37.65	31.95	38.87
% University	4.46	3.90	5.26
% Blue collars	67.54	67.02	66.41
% White collars	23.40	23.15	26.93
		Innovation capacity	
Do R&D	33.29	37.41	46.41
Invested in ICT	76.13	82.12	79.65
Innovating products	29.83	25.63	41.0
Innovating process	66.16	22.01	17.88
% formal training	2.66	3.98	4.99
		Other characteristics	
Age	23.4	24.4	28.1
		Made in Italy	
Food	0.10	8.57	11.26
Clothing, Textile	9.99	0.07	7.74
Machinery	16.93	13.15	14.28

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Table 2: OIs conditional on firms characteristics

	1995-1997	1998-2000	2001-2003	Panel
OI_pd	11.59	11.60	19.99	15.48
OI_pc	22.87	19.02	14.77	17.80
OI_pd | large firms	25.58	17.83	25.85	26.21
OI_pc | large firms	36.79	21.74	15.89	27.43
OI_pd | R&D firms	21.16	22.44	34.48	28.74
OI_pc | R&D firms	34.92	24.40	15.92	22.36
OI_pd | HTech	13.92	16.59	25.02	21.53
OI_pc | HTech	23.78	21.03	12.91	18.66
OI_pd | OI_pc	36.96	6.24	12.32	19.92
OI_pc | OI_pd	72.94	10.23	9.10	22.91
OI_pd | TI_pd or TI_pc	14.60	22.63	31.34	24.68
OI_pc | TI_pd or TI_pc	29.18	26.44	19.92	23.71
Total firms	4495	3034	4178	1883

Table 3: OIs conditional on current TIs

	1995-1997	1998-2000	2001-2003
OI_pd | TI_pd	35.78	39.88	42.50
OI_pc | TI_pd	36.39	7.32	6.67
OI_pd & OI_pc | TI_pd	29.36	26.01	30.00
Observations	981	1557	1800
OI_pd | TI_pc	16.94	3.68	4.02
OI_pc | TI_pc	33.58	46.08	42.41
OI_pd & OI_pc | TI_pc	14.39	2.94	3.12
Observations	2001	1224	672

Percentage values calculated within the panel.

Table 4: TIs conditional on current OIs

	1995-1997	1998-2000	2001-2003
TI_pd | OI_pd	84.78	86.61	90.42
TI_pc | OI_pd	81.88	6.28	3.19
Observations	414	717	846
TI_pd | OI_pc	48.97	10.89	24.10
TI_pc | OI_pc	92.18	53.87	57.23
Observations	729	1047	498

Percentage values calculated within the panel.

Table 5: OIs conditional on past wave TIs

	1998-2000	2001-2003
OI_pd | past wave TI_pd	22.63	29.36
OI_pc | past wave TI_pd	16.82	9.26
OI_pd & OI_pc | past wave TI_pd	14.98	22.49
Observations	981	1134
OI_pd | past wave TI_pc	16.49	21.27
OI_pc | past wave TI_pc	18.74	15.56
OI_pd & OI_pc | past wave TI_pc	11.09	16.19
Observations	2001	945

Percentage values calculated within the panel.

Table 6: TIs conditional on past wave OIs

	1998-2000	2001-2003
TI_pd | past wave OI_pd	55.80	70.59
TI_pc | past wave OI_pd	15.22	10.59
Observations	414	510
TI_pd | past wave OI_pc	41.15	47.66
TI_pc | past wave OI_pc	20.99	19.53
Observations	729	768
TI_pd | past wave OI_pd & OI_pc	60.40	70.08
TI_pc | past wave OI_pd & OI_pc	14.85	12.82
Observations	303	351

Percentage values calculated within the panel.

Table 7: Transitional matrix of OIs related to product in the panel

past wave OI_pd	OI_pd		Total
	no	yes	
no	72.88 (5,193)	14.15 (1,008)	87.03 (6,201)
yes	8.93 (636)	4.04 (288)	12.97 (924)
Total	81.81 (5,829)	18.19 (1,296)	100.00 (7,125)

Table 8: Transitional matrix of OIs related to process in the panel

past wave OI_pc	OI_pc		Total
	no	yes	
no	68.51 (4,881)	10.48 (747)	78.99 (5,628)
yes	17.22 (1,227)	3.79 (270)	21.01 (1,497)
Total	85.73 (6,108)	14.27 (1,017)	100.00 (7,125)

Table 9: Logit of OIs related to product

	1995-97	1998-00	2001-03
		Size	
ln(Sales)	.157*** (.056)	.074 (.085)	.148*** (.050)
		Profitability	
Operating Profits p.w.	-.001 (.004)	.012 (.011)	-.005 (.004)
Cashflow p.w.	.002 (.003)	-.010 (.010)	.004 (.004)
		External activity	
Group	.104 (.136)	.244 (.193)	-.197* (.114)
Export	.225 (.153)	.274 (.236)	.117 (.132)
		Skills endowment	
% R&D workers	-.897 (1.266)	2.173** (1.029)	2.526*** (.726)
% Junior-high	.835 (2.034)	.929** (.431)	31.058 (22.723)
% High-school	-.751 (2.051)	-	31.197 (22.722)
% University	1.210 (2.144)	1.567 (1.177)	32.373 (22.718)
% Blue collars	3.023*** (1.104)	1.087 (1.245)	.509 (.658)
% White collars	3.712*** (1.191)	1.092 (1.379)	.298 (.714)
		Innovation capacity	
Do R&D	.831*** (.134)	.787*** (.231)	1.020*** (.119)
Invested in ICT	.668*** (.171)	.694** (.297)	.648*** (.142)
% formal training	.818* (.469)	1.054* (.595)	.857** (.343)
		Other characteristics	
Age	.003 (.003)	-.003 (.005)	.001 (.002)
Constant	-8.482*** (2.299)	-4.713** (1.176)	-37.307* (22.752)
		Made in Italy	
Food	-	-.465 (.414)	1.122 (1.093)
Clothing, Textile	.658** (.271)	-	1.657 (1.097)
Machinery	.539** (.261)	-.622* (.363)	1.492 (1.090)
Number of firms	3450	1146	3034
pseudo-R^2	0.108	0.07	0.113

Sector and area dummies are included. Standard errors in parentheses. *** significant at 1% level, ** 5%, * 10%.

Table 10: Logit of OIs related to process

	1995-97	1998-00	2001-03
		Size	
ln(Sales)	.043 (.045)	.050 (.081)	.094* (.052)
		Profitability	
Operating Profits p.w.	.002 (.003)	-.002 (.011)	-.010** (.004)
Cashflow p.w.	-.0001 (.002)	-.003 (.009)	.009** (.004)
		External activity	
Group	.187* (.108)	-.070 (.193)	.206* (.119)
Export	.239** (.109)	-.403** (.202)	-.021 (.123)
		Skills endowment	
% R&D workers	1.159 (.939)	-.963 (1.049)	-1.09 (.958)
% Junior-high	.576 (1.750)	-.466 (.377)	-44.98** (21.62)
% High-school	-.688 (1.759)	-	-45.30** (21.62)
% University	.620 (1.842)	.481 (1.165)	-45.02** (21.63)
% Blue collars	1.663** (.710)	.930 (1.048)	-.218 (.648)
% White collars	1.597** (.780)	.961 (1.175)	-.100 (.714)
		Innovation capacity	
Do R&D	.640*** (.105)	.393** (.195)	-.046 (.123)
Invested in ICT	.624*** (.117)	.641** (.264)	.126 (.126)
% formal training	2.290*** (.416)	.562 (.599)	.635* (.349)
		Other characteristics	
Age	.0001 (.002)	-.002 (.005)	.002 (.003)
Constant	-4.758** (1.883)	-1.712 (1.752)	42.56** (21.63)
		Made in Italy	
Food	-	-.490 (1.459)	.120 (.669)
Clothing, Textile	-.185 (.197)	-	.371 (.682)
Machinery	-.289 (.185)	-.780 (1.451)	-.102 (.676)
Number of firms	3450	1129	3034
pseudo-R^2	0.089	0.04	0.024

Sector and area dummies are included. Standard errors in parentheses. *** significant at 1% level, ** 5%, * 10%.

Table 11: Labor productivity growth regressions: Model 1

$\Delta \ln y_{it}$	Model 1				
	OLS	IV	BE	IVBE	$E(X\varepsilon) = 0$
$\Delta \ln k_{it}$	.15***	.13**	.11***	.11***	[.024]**
	(.026)	*(.066)*	*(.018)*	*(.068)*	
OI_pc (δ)	.003	.42*	.006	.42*	[.286]
	(.011)	*(.252)*	*(.014)*	*(.225)*	
OI_pd (δ)					
Cons	-.029	-.089**	.008	-.036	
R^2	.027	.03	.07	.04	
Hausman		[.00]***	[.96]	[.00]***	
N	6768	3941	6768	3941	

Area, size and sectors dummies are included in all regressions. Both capital stock and OIs are instrumented under IV and IVBE methods. *** significant at 1% level, ** 5%, * 10%. Standard errors in parentheses. p-values in brackets. Hausman test refers to comparison with estimation on the closest left column (H_0 : difference in coefficients not systematic between next columns). Weak exogeneity of the main regressors in OLS model is tested, and the p-value is reported under $E(X\varepsilon) = 0$. Instruments for $\Delta \ln k_{it}$ are: $lnY_{it-2}, \ln K_{it-2}, \ln(\text{non-R\&D-workers})_{it-2}$; for OI_pc they are: cash flow per worker, operating profits per worker, export dummy, R&D dummy, %investment in ICT, % trained workers; for OI_pd they are: group dummy, export dummy, % workers in R&D activity, Investment in ICT dummy, % trained workers. N is the number of observations in the unbalanced panel which fit the specific regression. IV methods are applied to a reduced sample because the instruments are not always available for all firms.

Table 12: Labor productivity growth regressions: Model 2

$\Delta \ln y_{it}$	Model 2				
	OLS	IV	BE	IVBE	$E(X\varepsilon)=0$
$\Delta \ln k_{it}$	.15***	.18**	.11***	.15**	[.169]
	(.026)	*(.085)*	*(.018)*	*(.063)*	
OI_pc (δ)					
OI_pd (δ)	.01	.15*	-.004	.15***	[.033]**
	(.011)	*(.082)*	*(.014)*	*(.048)*	
Cons	-.029	.026	.009	.034	
R^2	.03	.02	.07	.03	
Hausman		[.00]***	[.090]*	[.00]***	
N	6768	3943	6768	3943	

See note under Table 11.

Table 13: Labor productivity growth regressions: Model 3 and 4

$\Delta \ln y_{it}$	Model 3				Model 4			
	OLS	IV	BE	IVBE	OLS	IV	BE	IVBE
$\Delta \ln k_{it}$	.15***	.14**	.11***	.14***	.15***	.18**	.11***	.15**
	(.026)	(.061)	(.018)	(.053)	(.026)	(.084)	(.019)	(.062)
OI_pc (δ)	.01	.31**	.003	.27**				
	(.011)	(.136)	(.014)	(.121)				
OI_pd (δ)					.01	.13	-.005	.13***
					(.011)	(.084)	(.014)	(.049)
TI_pd ($\alpha\gamma_1$)	.014	.079***	-.015	.075***				
	(.009)	(.028)	(.011)	(.025)				
TI_pc ($\alpha\gamma_1$)					-.005	.018	-.005	.012
					(.010)	(.024)	(.012)	(.016)
Cons	-.032	-.29	.011	-.235	-.024	.008	.014	.021
γ_1	.091	.56	-.13	.55*	-.030	.099	-.04	.08
	(.060)	(.354)	(.100)	(.319)	(.064)	(.151)	(.105)	(.117)
R^2	.03		.07	.02	.03	.03	.07	.03
Hausman	[1.00]	[1.00]	[.173]	[.667]	[1.00]	[1.00]	[.681]	[.537]
N	6768	3941	6768	3941	6768	3943	6768	3943

Area, size and sectors dummies are included in all regressions. Both capital stock and OIs are instrumented under IV and IVBE methods. Instruments for $\Delta \ln k_{it}$ are: $lnY_{it-2}, \ln K_{it-2}, \ln(\text{non-R\&D-workers})_{it-2}$; for OI_pc they are: cash flow per worker, operating profits per worker, export dummy, R&D dummy, %investment in ICT, % trained workers; for OI_pd they are: group dummy, export dummy, % workers in R&D activity, Investment in ICT dummy, % trained workers. *** significant at 1% level, ** 5%, * 10%. Standard errors in parentheses, p-values in brackets. Hausman tests compare Model 3 with nested Model 1 and Model 4 with nested Model 2 (H_0 : difference in coefficients not systematic in nested regressions).

Table 14: Labor productivity growth regressions: Model 5 and 6

$\Delta \ln y_{it}$	Model 5				Model 6			
	OLS	IV	BE	IVBE	OLS	IV	BE	IVBE
$\Delta \ln k_{it}$	.15***	.14**	.11***	.13**	.15***	.16**	.11***	.15**
	(.026)	(.063)	(.019)	(.060)	(.026)	(.088)	(019)	(.062)
OI_pc (δ)	.007	.47**	.007	.43**				
	(.011)	(.203)	(.015)	(.187)				
OI_pd (δ)					.003	-.061	.007	.051
					(.012)	(.148)	(.016)	(.077)
TI_pd ($\alpha\gamma_1$)	.013	.051***	-.017	.053***				
	(.009)	(.019)	(.011)	(.020)				
TI_pc ($\alpha\gamma_1$)					-.002	.-.003	-.010	-.008
					(.010)	(.020)	(.012)	(.014)
TI_pc ($\beta\gamma_2$)	-.004	-.168**	-.012	-.144**				
	(.010)	(.074)	(.013)	(.067)				
TI_pd ($\beta\gamma_2$)					.011	.036	-.021*	-.007
					(.010)	(.064)	(.012)	(.033)
Cons	-.028	-.281	.024	-.244	-.029	.040	.023	.045
γ_1	.084	.361	-.156	.42	-.010	-.017	-.089	-.052
	(.063)	(.232)	(.103)	(.279)	(.068)	(.120)	(.108)	(.096)
γ_2	-.004	-.195**	-.013	-.165**	.013	.043	-.023*	-.008
	(.012)	(.083)	(.014)	(.074)	(.012)	(.075)	(.014)	(.039)
R^2	.03		.07		.03	.003	.07	.08
Hausman 1 or 2	[1.00]	[1.00]	[.255]	[.745]	[1.00]	[1.00]	[.251]	[.107]*
Hausman 3 or 4	[1.00]	[1.00]	[.350]	[.482]	[1.00]	[1.00]	[.107]*	[.044]**
N	6768	3941	6768	3941	6768	3943	6768	3943

See note in Table 13. Model 1 and 3 are nested into Model 5. Model 2 and 4 are nested into Model 6. Hausman tests Model 5 versus Model 1 or 3 in the first 4 columns, and it tests Model 6 versus Model 2 or 4 in the last 4 columns.