From outsourcing to productivity, passing through training: microeconometric evidence from Italy

Roberto Antonietti
Department of Economics and Management "Marco Fanno"
Via del Santo 33
35123 Padova, Italy
E-mail: roberto.antonietti@unipd.it

Abstract

The aim of this paper is to provide firm-level evidence on the short-run link between outsourcing and labor productivity using an original dataset of Italian manufacturing firms, and applying a two-stage probit least squares estimator. We find a positive effect on productivity from outsourcing only if firms provide training for the workforce. This indirect impact on productivity is independent of the type of activity outsourced and is bigger in the case of service outsourcing. This can be explained by the different feedback effect of labor productivity on training and by the different type of training provided. While production outsourcing induces an organizational change which stimulates off-the-job training for plant operators, service outsourcing induces firms to train a broader range of occupational profiles - both off and on the job. Similar results emerge for the case of joint outsourcing of both production and service activities. Therefore, we find that outsourcing generates positive productivity effects only if it is part of a broader knowledge management strategy that involves upgrading of workers' skills.

Keywords: outsourcing; productivity; training; two-stage probit least squares

JEL: J24, L24, L25, L60

Acknowledgments

I thank Sandro Montresor and Giulio Cainelli for useful comments on a previous version of the paper. I also thank the School of Development Innovation and Change (SDIC) for the provision of the dataset.

1. Introduction

Does outsourcing spur or hamper productivity? The answer to this question is still being debated by economists. Industry-level studies suggest a positive relationship between (material and service) outsourcing and manufacturing productivity (Egger et al., 2001; ten Raa and Wolff, 2001; Heshmati, 2003; Amiti and Wei, 2009). However, the evidence from firm-level studies is less clear (Olsen, 2006). Some works find a positive and significant effect of outsourcing on firm performance (Görzig and Stephan, 2002; Heshmati, 2003; Girma and Görg, 2004; Görg and Hanley, 2005), while others find no effect at all (Gilley and Rashid, 2000; Mol et al., 2004; Bengtsson and Dabhilkar, 2009).

These ambiguous results might be due to the different time horizons analyzed (Egger and Egger, 2006), the types of activity outsourced (Miozzo and Grimshaw, 2005; Daveri and Jona-Lasinio, 2008; Montresor et al., 2009), the industry and the geographical scope of outsourcing (Fixler and Siegel, 1999; Calabrese and Erbetta, 2005; Lo Turco, 2007; Görg et al., 2008), the degree of firm internationalization (Kimura, 2002; Tomiura, 2005; Montresor et al., 2009), the outsourcing measures used (Daveri and Jona-Lasinio, 2008), and the characteristics of the local production system in which the outsourcing firm is embedded (Montresor et al., 2009).

Windrum et al. (2009) propose an interesting alternative explanation for the outsourcing-productivity paradox, which links the outsourcing decision to organizational change. Relying on the modular theory of the firm, they argue that the positive effects of total outsourcing on productivity growth materialize only after managers have identified the organizational architectures that most efficiently combine the externalities from value-adding activities such as research and development (R&D), design, production and marketing. So, the effect of outsourcing on productivity growth passes through organizational innovations that take the form of new modules in which the positive externalities from closely related activities are maximized.

In this paper, we propose a different but complementary, argument. Since outsourcing may lead to a re-organization of production - and a new internal division of labor caused by wage, functional and/or numerical flexibility (Benson and Ieronimo, 1996; Murphy, 2002) – its short-run effect on productivity will depend on workers' capabilities to learn, absorb and effectively implement the organizational change. One of the main channels through which learning occurs within the firm is training. The idea behind this paper is that outsourcing generates positive productivity effects only if it part of a broader knowledge management strategy involving skills training. This notion complements Windrum et al. s' argument about the role of managers in the search for new and efficient organizational structures, by suggesting that training represents one way that outsourcing-induced organizational change translates into real productivity gains.

This idea is partly aligned to Bengtsson and Dabhilkar's (2009) thesis that firm performance depends on other manufacturing strategies that firms apply when outsourcing. However, we would suggest the crucial aspect is the organizational change induced by outsourcing and the capability of this a new organizational setting to stimulate skills upgrades through training.

The link between outsourcing and training emerges in several empirical studies. While most research focuses on understanding how the introduction of new organizational practices increase the absolute and relative demand for skilled labor (Brynjolfsson and Hitt, 2000; Caroli, 2001; Caroli and Van Reenen, 2001; Caroli et al., 2001; Bresnahan et al., 2002; Piva et al., 2005), the link between organizational change and other forms of human capital, such as training, has been less thoroughly investigated. In a study of Italian manufacturing, Antonelli et al. (2010) find that outsourcing positively affects both the likelihood that firms will provide in-house training and the number of employees under training. Guidetti and Mazzanti (2007) and Antonioli et al. (2011) focus on manufacturing firms in the Modena and Reggio Emilia local production systems in the Emilia Romagna region of Italy and provide additional evidence of a positive link between organizational innovation, human resource practices, and firm-provided training. These results hold also in the case of Swiss firms: Hollenstein and Stucki (2012) document that while the propensity to work in teams positively affects the likelihood of training, its intensity is increased by changes to the hierarchical structure of the firm.

The positive productivity effects of training are acknowledged in many empirical studies. For example, Groot (1999) finds that trained workers show an average increase of 8% in productivity with respect to non-trained colleagues, while Barrett and O'Connell (2001) in a study of Irish establishments in the 1990s, find a positive and statistically significant productivity effect only for general or combined general-specific training but no relevant effect for specific training. For British establishments in the period 1988-1996, Schonewille (2001) find a positive productivity effect for training, significant at 10%. For Italy, Conti (2005) provides panel evidence of a positive effect of training on labor productivity in the period 1996 to 1999. Dearden et al. (2006) using data for a panel of British firms in 1983-1996, estimate that a 1% increase in training provision generates a 0.6% increase in average labor productivity. Finally, Almeida and Carneiro (2009) study a panel of large firms in Portugal, and taking account of training costs, find an estimated +8.6% return on productivity for firms that provide training.

To test the outsourcing-training-productivity relationship, we use an original dataset of Italian manufacturing firms which links information on outsourcing with data on training. Since firms may self-select into outsourcing, and the training-productivity relationship might be affected by simultaneity bias, we use a two-stage model. In the first stage, we estimate an outsourcing equation where the decision to outsource is explained by a set of firm, industry and geographic characteristics. In the second stage, we use the predicted value of outsourcing as a regressor, in a system of two simultaneous equations, to control for the feedback effects of labor productivity on training.

The estimation results conform the hypothesis proposed in this paper: after controlling for self-selection and reverse causality, outsourcing has a significant indirect effect on labor productivity, which is mediated by induced training. I find also that this indirect relationship does not depend on the type of activity being outsourced, although its intensity depends on the type of training provided. This is evidence that outsourcing is not always detrimental to firm performance and can generate positive outcomes if it is part of a broader firm re-organization strategy that stimulates learning and competence accumulation in workers.

The rest of the paper is organized as follows. Section 2 presents the empirical model and the econometric strategy; Section 3 describes the data; Section 4 discusses the estimation results; and Section 5 concludes.

2. The empirical model

Figure 1 depicts the structure of the model. It comprises two steps and three equations. In the first step, we estimate an outsourcing equation identifying the main variables related to the propensity to subcontract production and/or service activities. The second step consists of a system of two simultaneous equations, one for training and one for labor productivity, which account for their reciprocal effects.

[FIGURE 1 about here]

2.1. First-stage: the outsourcing equation

The first equation depicts firm's outsourcing behavior. Since not all firms contract out activities, and since the outsourcing choice has various motivations, the productivity estimates might be affected by selectivity bias. According to Bengtsson and Dabhilkar (2009, p. 254): "outsourcing motives and effects should not be analyzed in isolation". Moreover, the relationship between outsourcing and training could potentially be affected by simultaneity bias. For these reasons, I first estimate an outsourcing equation in which the probability to subcontract production or service activities is related to a specific set of determinants.

According to Abraham and Taylor (1996), three variables can potentially affect the likelihood to outsource. The first is labor costs. It is acknowledged in the literature that one of the strongest motivations for externalizing activities is labor cost savings. Therefore, we would expect high-wage firms to have a higher propensity to outsource their activities. However, if outsourcing occurs between similar firms, or follows a networking strategy rather than a search purely for lower wages, the effect of these costs can be insignificant for firms' outsourcing behavior (Taymaz and Kiliçaslan, 2005).

The second variable is related to the need to deal with market uncertainty, and to smooth the workload of the regular workforce. Relying on the assumption that organizations prefer a steady flow of work, we would expect that firms facing higher uncertainty in output demand will be more likely to outsource their production or service activities than firms operating in more stable environments. Conversely, it might be that higher market uncertainty leads firms to integrate activities in order to minimize the risks and costs associated with re-contracting.

The third determinant is local availability of specialized suppliers. If there is a shortage of internal skills, and/or if scale economies can be achieved from external provision of specialized services, firms may find it more profitable to externalize their activities. Abraham and Taylor (1996) capture this effect using two variables: firm size – based on the idea that small firms are more likely to subcontract than larger ones, and firm location in a dense urban area because availability of suppliers will be higher and the cost of outsourcing lower (Ono, 2007).

We include a fourth determinant of outsourcing, i.e. technology. According to recent studies, rapid technological change and innovation make outsourcing beneficial for firms because of the reduced time to amortize the sunk costs associated with purchase of new technology (Bartel et al., 2012), or because it allows the firm to focus on innovative activities and exploit its core competencies (Antonietti and Cainelli, 2008; Mazzanti et al., 2009).[1]

Based on these premises, the first-stage equation takes the following form:

$$OUT_i = f\,(SIZE_i,\ ULC_i,\ TECHNOLOGY_i,\ UNCERTAINTY_S,\ AREA) \qquad [1]$$

where *OUT* is a dummy variable that equals 1 if firm *i* outsources an activity previously developed in-house and 0 otherwise, and refers to the period 2001-2003. Since the dataset allows to differentiate between outsourcing of production and outsourcing of service activities, we re-estimate equation 1 using a dummy for outsourcing only of production activities (*OUT_PROD*), a dummy for outsourcing only service activities (*OUT_SERV*), and a dummy for outsourcing production and service activities jointly (*OUT_JOINT*).

Firm size (*SIZE*) is represented by a vector of three dummy variables - for small firms (11-50 employees), for medium-sized firms (51-250 employees), and for large firms (more than 250 employees), used as the reference category. *ULC* is the (log) labor cost per employee[2] in 2001. *TECHNOLOGY* is a vector of two innovation input variables, namely (log) of total R&D expenditure per employee (*R&D*), and investments in new machinery and equipment per employee (*M&E*), both measured in year 2001 to avoid simultaneity with the dependent variable.

To measure *UNCERTAINTY*, we use the index proposed by Fan (2000), which computes the standard deviation of residuals from the following de-trending equation:

[1] Mazzanti et al. (2009) provide a comprehensive survey on the drivers of outsourcing decisions. Here, we focus only on those variables that can be utilized in the estimates because of limitations on data availability.

[2] According to Abraham and Taylor (1996), an average measure of unit wages (or labor cost) can be a misleading indicator of the firm’s position in the wage hierarchy, because it can reflect either differences in wage rates for similar works, or differences in the skill level of the work performed. Unfortunately, the dataset provides information on yearly labor cost, without distinguishing among types of occupation.

$$IPI_{S,t} = \beta_0 + \beta_1 t + \varepsilon_{S,t} \qquad [2]$$

where *IPI* is the Industrial Production Index for sector *S* in year *t,* and *ε* is the error component. In line with Abraham and Taylor (1996), and in the absence of quarterly data on sales or employment, we use yearly information on industrial production at the level of the 13 two-digit manufacturing sectors to which the firm belonged over the period 1991-2000. As already explained, the sign of *UNCERTAINTY* on *OUT* is expected to be ambiguous.

Finally, we control for two characteristics of the area (*AREA*) in which the firm is located. The first is a set of four dummy variables capturing the macro-area in which the firm is located, i.e. NUTS-1 regions North West, North East, Center and South of Italy, with South of Italy used as the reference category. Since we do not have information at a finer geographical scale, we compute an index for degree of "districtization" of the NUTS-2 region. This index (*DISTRICT REGION*) is given by the ratio between manufacturing employment in the local labor systems classified as industrial districts in region *R* (in 1991), and total manufacturing employment in region *R* (as computed in De Arcangelis and Ferri, 2005). The higher this index, the higher the presence and weight of industrial districts in the region, which should facilitate outsourcing due to the higher local availability of specialized suppliers typical of the industrial district model based on flexible specialization (Brusco, 1982).

Since the dependent variable is binary, we estimate equation 1 employing a probit model; from this, we extract the predicted value of outsourcing, *Pred*(*OUT*). Then we estimate three separate probit models for *OUT_PROD*, *OUT_SERV and OUT_JOINT*, from which we take the three linear predicted values, *Pred*(*OUT_PROD*), *Pred*(*OUT_SERV*) and *Pred*(*OUT_JOINT*)[3].

[3] Because of the presence of firms that jointly outsource product and service activities, as a robustness check we also estimated a bivariate probit model. The results are presented in Appendix Table A1 and are qualitatively the same.

2.2. Second-stage: the training and productivity equations

In the second stage, we estimate two simultaneous equations, one for training and one for labor productivity to account for the feedback effects of the latter on the former.

The two equations are defined as follows:

$$TRAINING_i = \beta_0 + \beta_1 \log\left(\frac{Y}{L}\right)_i + \beta_2 \,\mathrm{Pred}(OUT)_i + \beta_3 Log\left(\frac{L^H}{L}\right)_i + \beta_4 Log\left(\frac{L^U}{L}\right)_i + \beta_5 CONTROLS_i^1 + u_i \quad [3]$$

$$\log\left(\frac{Y}{L}\right)_i = \gamma_0 + \gamma_1 TRAINING_i + \gamma_2 Log\left(\frac{K}{L}\right)_i + \gamma_3 Log\left(\frac{L^H}{L}\right)_i + \gamma_4 Log\left(\frac{L^U}{L}\right)_i + \gamma_5 CONTROLS_i^2 + \eta_i \quad [4]$$

In equation 3, the dependent variable *TRAINING* is a dummy equal to 1 if firm *i* provided training for its workforce in year 2003. Since the dataset gathers information on the type of occupational profile to which training is targeted, we consider three dummies that represent the following types of training: training for managers (*TRAIN_MAN*), training for executives and middle managers (*TRAIN_EXE*), and training for plant operators (*TRAIN_PO*). The dataset also provides information on place and type of training, i.e. formal in-house, formal external, and informal on-the-job in the form of coaching. We identify two dummy variables to capture formal off-the-job (*TRAIN_OFF*) and informal on-the-job training (*TRAIN_ON*).

Following the literature on the determinants of training (Bassanini et al., 2007; Antonelli et al., 2010; Ciriaci, 2011, Hollenstein and Stucki, 2012), among the regressors we include the value of outsourcing predicted by equation 1, labor productivity in 2003 (log(Y/L)), the share of skilled L^H/L (i.e. white collar workers - managers, executives and clerks) and unskilled labor L^U/L (i.e. plant operators), and controls for firm size, industry and location - macro-area (NUTS-1 region).

In equation 4, the dependent variable is given by the log value added per employee in 2003, and the regressors include the *TRAINING* dummy variable, the log share of skilled L^H/L and unskilled labor L^U/L, the log of the capital-labor ratio K/L in 2001, and controls for firm size, export status (in 2001-2003), industry, and macro-area of localization[4].

Since both training and labor productivity are observed in year 2003, potential simultaneity bias could affect standard ordinary least squares (OLS) estimates of equation 4. One of our two endogenous variables is binary so a standard three-stage least squares approach cannot be utilized. To address this issue, we use the two-stage estimation method developed by Amemiya (1978), Heckman (1978) and Maddala (1983) for simultaneous equation models, in which one of the endogenous variables is continuous and the other is dichotomous,[5] which renders all the estimated coefficients consistent and the corresponding standard errors corrected for the inclusion of predicted values. Appendix 1 provides additional details on this econometric methodology.

3. The dataset

Data are extracted from the merging of two data sources: the 9th wave of the Unicredit Survey of manufacturing firms, and Excelsior data provided by Italian Chambers of Commerce (*Centro Studi Unioncamere*).

The 9th survey on manufacturing firms gathered information on a representative sample of 4,289 manufacturing firms across the 2001-2003 period. While firms with more than 500 employees are fully represented, those with more than 10 and fewer than 500 employees are

---

[4] In a different specification of equation 4, we included variables for product and process innovation but they were never statistically significant and potentially could be correlated with predicted outsourcing through R&D. We chose the most parsimonious version of the simultaneous model in order to reduce collinearity problems across stages while maintaining identification conditions.

[5] In effect, I estimate a two-stage probit least squares model using the Stata13 routine, *cdsimeq,* developed by Keshk (2003).

selected based on their geographical location, size and Pavitt industry. The survey includes rich information on firm characteristics and activities. For the present study, we exploit information on firm size, industry, area, labor force composition, innovation and export activities.

Excelsior data are compiled by the Italian Chambers of Commerce in collaboration with the Italian Ministry of Labor and the European Social Fund. They provide information on predicted demand for labor as well as actual employment, for a representative sample of some 100,000 private companies with more than 1 employee, distributed across Italy (Centro Studi Unioncamere, 2007). The data are organized according to four categories: (i) annual predicted employment inflows and outflows by type of occupational profile (i.e. managers, clerks and plant operators), (ii) characteristics and qualifications of new job applicants, such as age, experience, education, gender, immigration status, type of labor contract, further training after recruitment, foreign language ability, and informatics skills, (iii) use of a-typical employment contracts, (iv) training activities provided by firms to their actual workforce. In this work, we use the information on training in year 2003.

Merging the two datasets results in a sample of 1,545 observations. Those with missing values for employment and balance sheet variables, negative value added and obvious inconsistencies were dropped. The final sample is composed of 1,410 firms, whose distribution is shown in Table 1.

[TABLE 1 about here]

While the industry and geographic distribution of firms is in line with census data, the size distribution is biased against small firms. This should be taken into account when discussing the estimation results, which apply more the cases of medium sized and large firms. This represents a limitation of this paper; however, medium and large firms account for almost 50% of national employment in Italy, and are the types of firms that are the most innovative and internationalized.[6]

Table 2 presents some summary statistics for the sample of outsourcing firms. The percentages in Columns 1 to 3 (Column %), show that outsourcing (both production and service) firms are predominantly medium-sized, are located in the North of Italy, and belong to traditional supplier-dominated and specialized supplier industries. Columns 4-6 show the frequency of outsourcing by size, area, and industry. In this case, the share of outsourcing firms is higher among small and large firms than medium-sized firms; the North East is the most outsourcing intensive area of Italy, and science-based industries are the most outsourcing intensive in the case of both production and service activities.

[TABLE 2 about here]

In general, 21.42% of firms outsource at least one activity: among these, 38.74% outsource only production activities, 42.05% outsource only service activities, and 19.21% outsource both types of activity. Among the service activities outsourced, almost 70% are knowledge-intensive (i.e. computing-related, R&D and engineering, testing and technical analysis, advertising) and the remaining 30% are traditional (administration, bookkeeping, call-center, janitorial services, storage).

4. Results

Tables 3 to 9 present the estimation results. Table 3 refers to the first-stage estimates. In this Table, Column 1 provides the results of the probit estimate of the probability to outsource in general, and

[6] For a detailed discussion of sample construction and representativeness, see Antonelli et al. (2010).

Columns 2 and 3 respectively provide the results for the probability to outsource only production, and only service activities. Column 4 provides the results for the probability to outsource both production and service activities.

[TABLE 3 about here]

Column 1 in Table 3 shows that the (general) propensity to outsource increases with market uncertainty, location in the Northern and Central regions (taken here as a sign of availability of local skills), R&D intensity, and investments in new machinery and equipment. Since the unit labor cost is never statistically significant, we argue that traditional motives related to cost saving are not relevant here. What matters more are the innovation-related variables, and market uncertainty.[7]

The picture is simpler when we distinguish between production and services outsourcing. The estimates in Table 3 Column 2 show that production outsourcing is related more to location (*AREA*) and size variables, i.e. to motivations related to internal skills shortages and/or external skills availability. This evidence is in line with previous studies showing that outsourcing occurs more frequently and more intensively, when firms are located in more dense market areas (Ono, 2007; Holl, 2008; Antonietti and Cainelli, 2008; Antonietti et al., 2012; Cainelli and Iacobucci, 2012). Estimates in Table 3 Column 3 show that service outsourcing is related more to innovation drivers such as R&D, capital-embodied technology, and large firm size. Column 4 shows that more complex outsourcing decisions involving both production and service tasks are driven by market uncertainty and R&D intensity. Therefore, these probit estimates seem to define three different outsourcing behaviors: behavior related to production activities is driven more by skill availability, behavior related to service activities is driven more by innovation determinants, and behavior

[7] The Hosmer and Lemeshow goodness of fit test does not reject the null hypothesis of correct specification of the empirical model.

related to outsourcing of both production and service activities is motivated more by market uncertainty and R&D.

As already explained, these estimates provide four predicted values - for outsourcing in general (*Pred_OUT)*, for production outsourcing (*Pred*(*OUT_PROD*)), for services outsourcing (*Pred*(*OUT_SERV*)), and for joint (production and service) outsourcing (Pred(*OUT_JOINT*)) – which are employed in the system of simultaneous equations (2) and (3).

Second-stage results are presented in Tables 4 to 9. Table 4 Columns 1 and 2 show the two-stage probit least squares results when *Pred_OUT* is used as a regressor. The results in Column 1 show that, after controlling for size, labor quality, capital intensity and exports, higher outsourcing-induced training strongly and positively influences the level of labor productivity. The main research hypothesis is confirmed that outsourcing is indirectly related to higher productivity only if firms provide training for their workforce. Column 2 shows that, other things being equal and controlling for the feedback effect of productivity, training propensity is positively and strongly related to outsourcing.

[TABLE 4 about here]

A refinement to this general result is shown in Table 4 Columns 3 to 8. Columns 3 and 4 present the results of the two-stage probit least squares estimates for production outsourcing; Columns 5 and 6 refer to service outsourcing; and Columns 7 and 8 refer to joint outsourcing. In all the three cases, outsourcing is positively and significantly (at the 1% level) related to training, and training is positively and significantly (at the 1% level) related to productivity. This confirms that the outsourcing-training-productivity relationship holds regardless of the type of outsourcing.[8] It is

[8] In separate estimates, we included the observed outsourcing dummy among the regressors in the second-stage to check for direct outsourcing effects on labor productivity. The estimated coefficient of outsourcing is never statistically

interesting that production outsourcing has the highest effect on training, but the lowest indirect impact on labor productivity. Conversely, service outsourcing has the lowest impact on training but the highest induced effect on labor productivity. The effect of joint outsourcing lies between these two.

A first explanation for this effect lies in the magnitude of the feedback effect of labor productivity on training: Table 4, Columns 4, 6 and 8 show that this effect is highest if the firm contracts out production activities, and lowest if it contracts out service activities. However, it might also be attributable to the different types of training provided. In particular, we control for the occupational profile to which training is targeted, distinguishing among managers, executives/middle managers, and plant operators, and the type of training provided, distinguishing between formal off-the-job and informal on-the-job training.

Tables 5, 6 and 7 provide estimation results for training targets. It is clear that the main training effect of production outsourcing is on plant operators (significant at 1%), followed by managers (significant at 10%), whereas there is no effect for executives and middle managers. In contrast, service outsourcing involves training for all types of workers and is more relevant for managers than plant operators and executives. A similar picture emerges for the joint outsourcing case: it increases the propensity to provide training for all the three occupational profiles, with a larger impact on plant operators and top managers. Therefore, service outsourcing seems to stimulate the development of a larger skills portfolio, involving particularly non-manual and less standardized tasks, while production outsourcing fosters the skills upgrading of manual workers, and the re-scheduling of more standardized tasks.

[TABLE 5 about here]

---

significant, as reported in Appendix, Table A2. Therefore, I submit that the productivity effect of outsourcing is only indirect.

[TABLE 6 about here]

[TABLE 7 about here]

Tables 8 and 9 show that the type of training matters for explaining the heterogeneous productivity impacts of outsourcing. In particular, we find that production outsourcing, on its own, has an impact on productivity via off-the-job training only, i.e. formal training in which the knowledge transferred is mainly codified, where direct and opportunity costs are higher, and where returns materialize more slowly. On the other hand, service (and joint) outsourcing increase productivity by inducing firms to provide both off-the-job and on-the-job training, with the latter typically involving the transmission of tacit and specific knowledge from a more experienced worker (a master) to a less experienced one (a pupil), at lower cost and with immediate productivity returns.[9] Moreover, unlike production outsourcing, service outsourcing is pushed by innovation-related drivers, so that training occurs in technologically advanced contexts where learning and skill acquisition are easier and more efficient (Antonelli et al., 2010; Ciriaci, 2011), and where training allows R&D to impact on firm productivity.

[TABLE 8 about here]

[TABLE 9 about here]

Figure 2 summarizes all the results, sketching the outsourcing models emerging from estimation results.

[9] Unfortunately, the data do not allow to distinguish between training of currently employed workforce and training of newly hired employees, or recruiting to fill vacant jobs because of retirement or dismissals. However, it is reasonable to assume that, in the short run, outsourcing is related more to a reduction than an expansion in the workforce at firm level. Thus, we assume here that training is more likely to be targeted to the existing workforce.

]FIGURE 2 about here]

Firms outsourcing production phases – motivated by internal skills shortages and/or external skill availability - are likely to induce a kind of organizational change which re-defines existing production-related tasks (e.g. through modularization) because of the reduction in the firm's productive base. The training needed in order to benefit from the new organizational structure is primarily targeted at plant operators. On the other side, service outsourcing – for innovation reasons – induces organizational change that reshapes the links between manufacturing and service activities, particularly knowledge-intensive ones. Thus, training involves not only plant operators but also top and intermediate managers. The situation for the joint outsourcing case is similar.

In our view, this explanation complements the results provided in Windrum et al., (2009): once firms outsource, they become more productive if managers can identify and select an organizational structure that more efficiently coordinates high value-added modules and *also* after workers have been trained so as to maximize the benefits deriving from the new organizational setting, the new internal division of labor, and the exploitation of existing core competencies. This supports a complementary role of external relations (i.e. through outsourcing) and knowledge management practices (i.e. through training) for fostering productivity (Murphy, 2002).

5. Conclusions

This paper explored the short-run relationship between outsourcing and labor productivity. It posits that outsourcing generates positive returns only if it is part of a broader organizational strategy that involves worker training. Using an original dataset of Italian manufacturing firms, a two-stage probit least squares model was estimated, accounting for self-selection into outsourcing and simultaneity in the training-productivity relationship. Evidence is found that, in the short run, outsourcing may be associated with higher levels of labor productivity. This positive link is indirect and mediated by a higher induced likelihood to train, independent of the outsourced activity and the motivations underlying the outsourcing decision.

To explain why service outsourcing, while being associated with a lower probability to train than production outsourcing is related also to higher productivity levels, we focus on two sources of training heterogeneity, i.e. training targeted at different occupational profiles, and formal off-the-job vs. informal on-the-job training. Two-stage probit least squares estimates show that while production outsourcing (driven by skills shortages) is related to a higher likelihood to train plant operators off-the-job, service and joint outsourcing (pushed by innovation and uncertainty) are more related to a higher propensity to train a larger portfolio of occupations, both off-the-job and on-the-job.

These results provide firm-level evidence of an interplay between production organization practices and knowledge management practices for fostering firm productivity. In this respect, outsourcing can be seen as a form of strategic flexibility where firms adopt a different form of workplace organization in order to improve their performance.

From a policy perspective, the paper argues that, if outsourcing is not oriented to increasing the firm's functional flexibility, its productivity returns are uncertain. On the other hand, if outsourcing is part of a broader organizational strategy aimed at improving internal efficiency through learning and skills upgrading, it can generate positive returns to productivity. Therefore, outsourcing should not be treated as a way just for firms to cut labor costs; it should be seen also as a tool for exploiting core competencies and fostering organizational change. In the latter case, policies should be oriented to helping firms adopt the complementary organizational practices that make outsourcing more profitable, with a particular focus on training.

We should refer to the scope of the analysis in this paper. The cross-sectional nature of the dataset and the high incidence of medium and large-sized firms means that the results are not fully generalizable or robust to endogeneity, so they should be considered robust correlations rather than causal relationships. However, the paper provides a new interpretative framework for explaining the outsourcing-productivity paradox, which could be applied to longitudinal as well as larger and more representative contexts.

References

Abraham, K.G. and Taylor, S.K. (1996), Firms' use of outside contractors: theory and evidence, *Journal of Labor Economics*, 14(3), 394-424.

Almeida, R. and Carneiro, P. (2009), The return to firm investments in human capital, *Labour Economics,* 16(1), 97-106.

Amemiya, T. (1978), The estimation of a simultaneous equation generalized probit model, *Econometrica*, 46(5), 1193-1205.

Amiti, M. and Wei, S. (2009), service offshoring and productivity: evidence from the US, *The World Economy*, 32(2), 203-220.

Antonelli, G., Antonietti, R. and Guidetti, G. (2010), Organizational change, skill formation, human capital measurement: evidence from Italian manufacturing firms, *Journal of Economic Surveys,* 2482), 206-247.

Antonietti, R. and Cainelli, G. (2008), Production outsourcing, organizational governance and firm's technological performance: evidence from Italy, *The IUP Journal of Managerial Economics,* 6(1), 51-69.

Antonietti, R., Ferrante, M.R. and Leoncini, R. (2012), Spatial agglomeration, production technology and the choice to make and/or buy: empirical evidence from the Emilia Romagna machine tool industry, *Regional Studies*, doi: 10.1080/00343404.2012.657169.

Antonioli, D., Manzalini, R. and Pini, P. (2011), Innovation, workers skills and industrial relations: evidence from firm-level Italian data, *Journal of Socio-Economics*, 40(3), 312-326.

Barrett, A. and O'Connell, P.J. (2001), Does training generally work? The returns to in-company training, *Industrial and Labor Relations Review*, 54(3), 647-662.

Bartel, A., Lach, S. and Sicherman, N. (2012), Technological change and the make-or-buy decision, *Journal of Law, Economics and Organization*, online first, doi: 10.1093/jleo/ews035.

Bassanini A., Booth A., Brunello G., De Paola M. and Leuven E. (2007), Workplace training in Europe, in Brunello G., Garibaldi P. and Wasmer E. (eds.), *Education and training in Europe*, Oxford University Press, Oxford.

Bengtsson, L. and Dabhlikar, M. (2009), Manufacturing outsourcing and its effect on plant performance – Lessons from KIBS outsourcing, *Journal of Evolutionary Economics*, 19, 231-257.

Benson, J., and Ieronimo, N. (1996), Outsourcing decisions: evidence from Australia-based enterprises, *International Labour Review*, 135, 59-73.

Bresnahan, T.F., Brynjolfsson, E. and Hitt, L.M. (2002), Information technology, workplace organization and the demand for skilled labor: firm level evidence, *Quarterly Journal of Economics*, 117(1), 339–376.

Brusco, S. (1982), The Emilian model: productive decentralization and social integration, *Cambridge Journal of Economics*, 6(2), 235-261.

Brynjolfsson, E. and Hitt, L.M. (2000), Beyond computation: information technology, organizational transformation and business performance, *Journal of Economic Perspectives*, 14(4), 23–48.

Cainelli, G., and Iacobucci, D. (2012), Agglomeration, related variety and vertical integration, *Economic Geography*, 88(3), 255-277.

Calabrese, G. and Erbetta, F. (2005), Outsourcing and firm performance: evidence from Italian automotive suppliers, *International Journal of Automotive Technology and Management,* 5(4), 461-479.

Caroli, E. (2001), New technologies, organizational change and the skill bias: what do we know?, in Petit, P. and Soete, L. (Eds.), *Technology and the future of European employment,* Cheltenham, Edward Elgar, 259-292.

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

Caroli, E., Greenan, N. and Guellec, D. (2001), Organizational change and skill accumulation, *Industrial and Corporate Change*, 10(2), 481-506.

Centro Studi Unioncamere (2007), *Rapporto Excelsior 2007*, Rome, Unioncamere.

Ciriaci, D. (2011), Intangible resources: the relevance of training for European firms' innovative performance, JRC-IPTS Working Paper on Corporate R&D and Innovation 2011-08, IPTS, Seville.

Conti, G. (2005), Training, productivity and wages, *Labour Economics,* 12(4), 557-576.

Crépon, B., Duguet, E. and Mairesse, J. (2008), Research, innovation and productivity: an econometric analysis at the firm level, *Economics of Innovation and New Technology,* 7, 115-158.

Daveri, F. and Jona-Lasinio, C. (2008), Off-shoring and productivity growth in the Italian manufacturing industries, *CES-ifo Economic Studies,* 54(3), 414-450.

De Arcangelis, G. and Ferri, G. (2005), La specializzazione dei distretti: dai beni finali ai macchinari del «made in Italy»?, in Signorini, L.F. and Omiccioli, M. (Eds.), *Economie locali e competizione globale*, Bologna, Il Mulino, 283-297.

Dearden, L., Reed, H. and Van Reenen, J. (2006), The impact of training on productivity and wages: evidence from British panel data, *Oxford Bullettin of Economics and Statistics*, 68(4), 397-421.

Egger, P. Pfaffermayr, M. and Wolfmayr-Schnitzer, Y. (2001), The international fragmentation of Austrian manufacturing: the effects of outsourcing on productivity and wages, *The North American Journal of Economics and Finance,* 12(3), 257-272.

Egger, H. and Egger, P. (2006), International outsourcing and the productivity of low-skilled labor in the EU, *Economic Inquiry*, 44(1), 98-108.

Fan, J.P.H. (2000), Price uncertainty and vertical integration: an examination of petrochemical firms, *Journal of Corporate Finance,* 6, 345-376.

Fixler, D. and Siegel, D. (1999), Outsourcing and productivity growth in services, *Structural Change and Economic Dynamics*, 10(2), 177-194.

Gilley, K.M. and Rasheed, A. (2000), Making more by doing less: an analysis of outsourcing and its effects on firm performance, *Journal of Management,* 26, 763-790.

Girma, S. and Görg, H. (2004), Outsourcing, foreign owndership, and productivity: evidence from UK establishment-level data, *Review of International Economics,* 128(5), 817-832.? Not in text

Görg, H. and Hanley, A. (2005), International outsourcing and productivity: evidence from the Irish electronics industry, *The North American Journal of Economics and Finance,* 16(2), 255-269.

Görg, H., Hanley, A. and Strobl, E. (2008), Symposium on firm-level adjustment to globalization: productivity effects of international outsourcing: evidence from plant.level data, *Canadian Journal of Economics*, 41(2), 670-688.

Görzig, B. and Stephan, A. (2002), Outsourcing and firm-level performance, DIW Discussion Paper 309.

Groot, W. (1999), Productivity effects of enterprise-related training*, Applied Economics Letters*, 6(6), 369-371.

Guidetti, G. and Mazzanti, M. (2007), Firm-level training in local economic systems: complementarities in production and innovation strategies, *Journal of Socio-Economics*, 36(6), 875-894.

Heckman, J.J. (1978), Dummy endogenous variables in simultaneous equation system, *Econometrica,* 46, 931-959.

Heshmati, A. (2003), Productivity growth, efficiency and outsourcing in manufacturing and service industries, *Journal of Economic Surveys,* 17(1), 79-112.

Holl, A. (2008), Production subcontracting and location, *Regional Science and Urban Economics*, 38, 299-309.

Hollenstein, H. and Stucki, T. (2012), The ‘new firm paradigm’ and the provision of training: the impact of ICT, workplace organization and human capital, *Swiss Journal of Economics and Statistics*, 148(4), 557-595.

Keshk, O.M.G. (2003), CDSIMEQ: a program to implement two-stage probit least squares, *Stata Journal,* 3(2), 1-11.

Kimura, F. (2002), Subcontracting and the performance of small and medium firms in Japan, *Small Business Economics*, 18(1-3), 163-175.

Lo Turco, A. (2007), International outsourcing and productivity in Italian manufacturing sectors, *Rivista Italiana degli Economisti*, 12(1), 125-145.

Maddala, G.S. (1983), *Limited-dependent and qualitative variables in econometrics,* Cambridge (MA), Cambridge University Press.

Mazzanti, M., Montresor, S. and Pini, P. (2009), What drives (or hampers) outsourcing? Evidence for a local production system in Emilia Romagna, *Industry and Innovation*, 16(3), 331-365.

Miozzo, M. and Grimshaw, D.P. (2005), Modularity and innovation in knowledge-intensive business services: IT outsourcing in Germany and the UK, *Research Policy,* 34(9), 1419-1439.

Mol, J.M., Pauwels, P.F.J., Matthyssens, P. and Quintens, L. (2004), A technological contingency perspective on the depth and scope of international outsourcing, *Journal of International Management,* 10(2), 287-305.

Montresor, S., Mazzanti, M. and Pini, P. (2009), Outsourcing and innovation: evidence from a local production system of Emilia Romagna, *Innovation: Management, Policy and Practice,* 9(3-4), 324-342.

Montresor, S., Antonioli, D., Mazzanti, M. and Pini, P. (2009), Outsourcing and firm productivity: evidence from an Italian local production system, OPENLOC Working Paper 7/2009.

Murphy, M. (2002), Organisational change and firm performance, OECD Science, Technology and Industry Working Papers 2002/14, OECD Publishing.

Olsen, K.B. (2006), Productivity impacts of offshoring and outsourcing, OECD Science, Technology and Industry Working Paper 2006/1, OECD, Paris.

Ono, Y. (2007), Market thickness and outsourcing services*, Regional Science and Urban Economics*, 37, 220-238.

Piva, M., Santarelli, E. and Vivarelli, M. (2005), The skill bias effect of technological and organisational change: evidence and policy implications, *Research Policy*, 34(2), 141–157.

Schonewille, M. (2001), Does training generally work? Explaining labor productivity effects from schooling and training, *International Journal of Manpower,* 22(1/2), 158-172.

Ten Raa, T. and Wolff, E.N. (2001), Outsourcing of services and the productivity recovery in U.S. manufacturing in the 1980s and 1990s, *Journal of Productivity Analysis,* 16, 149-165.

Tomiura, E. (2005), Foreign outsourcing and firm-level charactiristics: evidence from Japanese manufacturers, *Journal of the Japanese and International Economies*, 19(2), 255-271.

Windrum, P., Reinstaller, A. and Bull, C. (2009), The outsourcing productivity paradox: total outsourcing, 22rganizational innovation, and long run productivity growth, *Journal of Evolutionary Economics,* 19, 197-229.

FIGURES

Figure 1. Model diagram

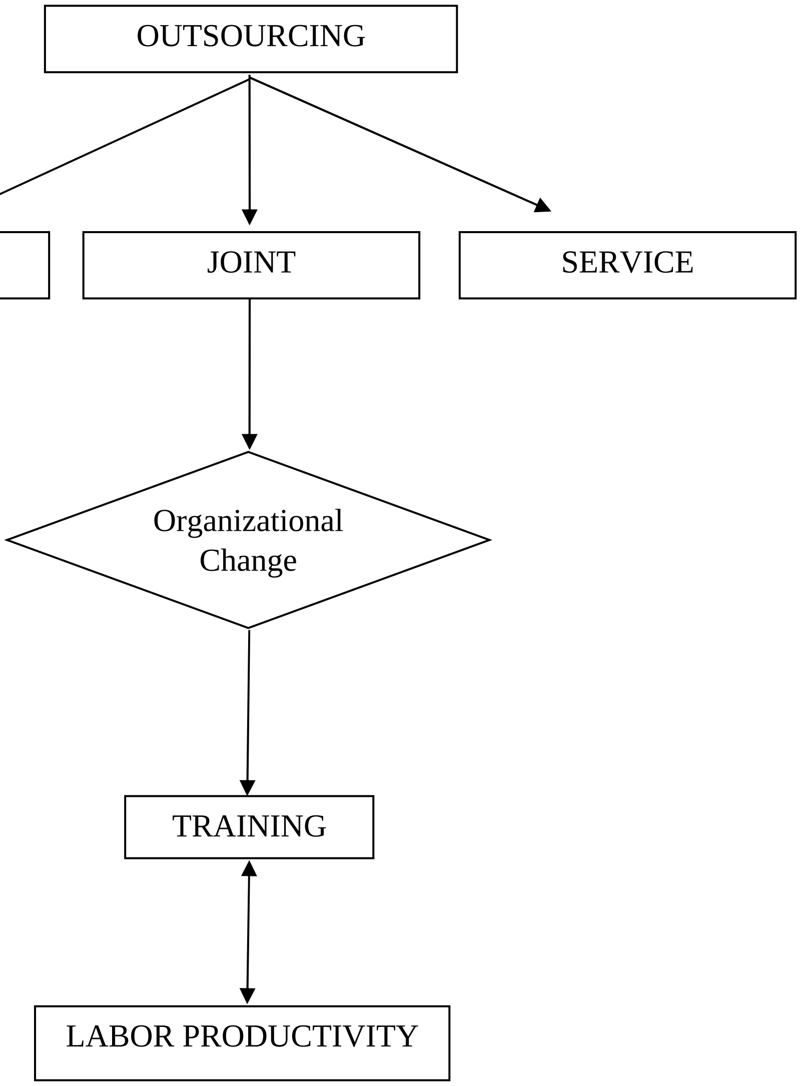
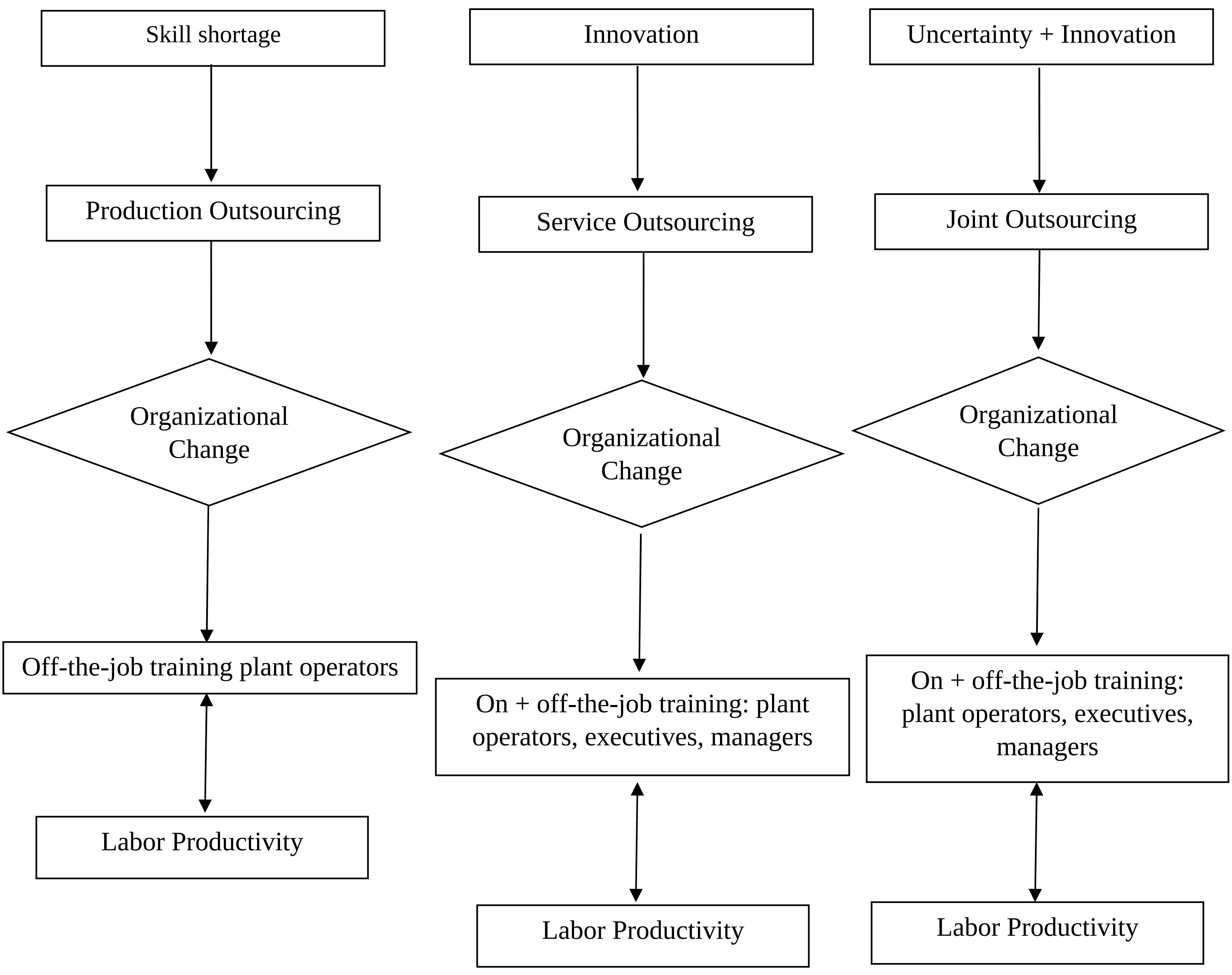


Figure 2. Outsourcing models from estimation results



TABLES

Table 1. Firm distribution by size, geographical area and industry

	Unicredit$_{2001\text{-}03}$		Before cleaning		After cleaning	
Firm size	**N.**	**%**	**N.**	**%**	**N.**	**%**
Small (11-50)	2217	51,7	306	19.81	287	20.35
Medium (51-250)	1584	36.9	862	55.79	790	56.03
Large (251+)	488	11.4	377	24.40	333	23.62
Area	**N.**	**%**	**N.**	**%**	**N.**	**%**
North West	1540	35.9	591	38.25	538	38.16
North East	1292	30.1	508	32.88	478	33.90
Centre	757	17.5	237	15.34	219	15.53
South	700	16.3	209	13.43	175	12.41
Industry (Pavitt classification)	**N.**	**%**	**N.**	**%**	**N.**	**%**
Supplier dominated	2228	51.9	705	45.63	645	45.74
Scale intensive	721	16.8	271	17.54	243	17.23
Specialized suppliers	1145	26.7	484	31.33	451	31.99
Science based	195	4.6	85	5.50	71	5.04
Total	**4289**	**100.0**	**1545**	**100.0**	**1410**	**100.0**

Table 2. Sample distribution of outsourcing firms

Firm size	Outsourcing Column %	OUTPROD Column %	OUTSERV Column %	Outsourcing Raw %	OUTPROD Raw %	OUTSERV Raw %
Small (11-50)	21.52	25.71	15.14	22.65	15.68	9.76
Medium (51-250)	52.98	54.29	52.43	20.33	12.12	12.37
Large (251+)	25.50	20.00	32.43	23.12	10.51	18.02
Area						
North West	39.07	41.71	38.38	22.08	13.73	12.25
North East	38.74	39.43	40.00	24.43	14.41	8.23
Centre	15.23	14.86	13.51	21.00	11.87	13.91
South	6.95	4.00	8.11	12.00	4.00	19.72
Pavitt Industry						
Suppl. dom.	42.72	45.14	40.00	20.00	12.25	11.47
Scale intensive	13.58	11.43	14.59	16.87	8.23	11.11
Specialized	36.09	35.43	37.30	24.28	13.91	15.45
Science based	7.62	8.00	8.11	32.39	19.72	21.13

Table 3. First stage estimates: probability to outsource

	[1] *OUT*	[2] *OUT_PROD*	[3] *OUT_SERV*	[4] *OUT_JOINT*
Uncertainty	0.012**	0.001	0.001	0.007***
	(0.006)	(0.004)	(0.004)	(0.002)
North West	0.105**	0.110***	-0.022	0.053
	(0.052)	(0.043)	(0.029)	(0.038)
North East	0.139**	0.123***	-0.002	0.060
	(0.059)	(0.050)	(0.034)	(0.045)
Centre	0.120*	0.146***	-0.001	0.027
	(0.067)	(0.066)	(0.036)	(0.046)
South	Ref.	Ref.	Ref.	Ref.
District Region	-0.058	-0.057	-0.010	0.020
	(0.065)	(0.042)	(0.044)	(0.026)
Small	0.028	0.090***	-0.032	-0.011
	(0.036)	(0.034)	(0.019)	(0.012)
Medium	-0.028	0.032	-0.040**	-0.008
	(0.028)	(0.020)	(0.018)	(0.010)
Large	Ref.	Ref.	Ref.	Ref.
ULC	-0.010	-0.019	0.017	-0.007
	(0.036)	(0.021)	(0.021)	(0.012)
R&D	0.010***	0.000	0.005**	0.003**
	(0.003)	(0.002)	(0.002)	(0.001)
M&E	0.012***	0.002	0.008***	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
N	1410	1410	1410	1410
Pseudo R^2	0.038	0.031	0.043	0.081
% corr. Class.	78.65	91.70	90.99	95.89
HL test (p-value)	0.488	0.503	0.409	0.909

Notes: cells report marginal effects at the mean of each dependent variable and for discrete changes of dummy variables from 0 to 1. A constant term is also included.
*** significant at 1%; ** significant at 5%; * significant at 10%. A constant term is also included in all the estimates. Standard errors are clustered at the level of each single observation.

Table 4. Second stage estimates: two-stage probit least squares

	[1] log(Y/L)	[2] Training	[3] log(Y/L)	[4] Training	[5] log(Y/L)	[6] Training	[7] Log(Y/L)	[8] Training
Training	0.226***		0.110***		0.135***		0.118***	
	(0.077)		(0.021)		(0.022)		(0.021)	
log(Y/L)		0.448*		0.519**		0.419		0.501*
		(0.262)		(0.258)		(0.269)		(0.258)
log(K/L)	0.153***		0.156***		0.151***		0.154***	
	(0.016)		(0.013)		(0.013)		(0.013)	
log(L^H/L)	0.269**	0.953**	0.280**	1.074**	0.261**	0.947**	0.273**	0.982**
	(0.124)	(0.439)	(0.122)	(0.438)	(0.126)	(0.440)	(0.124)	(0.443)
log(L^U/L)	-0.662***	0.383	-0.667***	0.418	-0.659***	0.399	-0.665***	0.434
	(0.118)	(0.440)	(0.115)	(0.435)	(0.119)	(0.444)	(0.117)	(0.441)
Export	-0.017		-0.011		-0.020		-0.014	
	(0.030)		(0.029)		(0.030)		(0.030)	
Pred(OUT)		0.518***						
		(0.162)						
Pred(OUT_PROD)				1.223***				
				(0.394)				
Pred(OUT_SERV)						0.426***		
						(0.153)		
Pred(OUT_JOINT)								0.448***
								(0.169)
Industry dummies	Yes		Yes		Yes		Yes	
Size dummies	Yes		Yes		Yes		Yes	
Area dummies	Yes		Yes		Yes		Yes	
N	1410		1410		1410		1410	
1st stage adj. R^2	0.373		0.369		0.376		0.371	
1st stage pseudo R^2	0.167		0.165		0.167		0.164	

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%. A constant term is also included in all the estimates.

Table 5. Second stage estimates: training of plant operators

	[1] log(Y/L)	[2] TrainPO	[3] log(Y/L)	[4] TrainPO	[5] log(Y/L)	[6] TrainPO	[7] log(Y/L)	[8] TrainPO
TrainPO	0.117***		0.103***		0.126***		0.110***	
	(0.020)		(0.019)		(0.020)		(0.019)	
log(Y/L)		0.764***		0.831***		0.750***		0.797***
		(0.277)		(0.273)		(0.281)		(0.270)
Pred(OUT)		0.483***						
		(0.162)						
Pred(OUT_PROD)				1.348***				
				(0.396)				
Pred(OUT_SERV)						0.335**		
						(0.153)		
Pred(OUT_JOINT)								0.482***
								(0.166)
N	1410		1410		1410		1410	
1st stage adj. R^2	0.373		0.369		0.376		0.370	
1st stage pseudo R^2	0.183		0.181		0.182		0.181	

Table 6. Second stage estimates: training of executives

	[1] log(Y/L)	[2] TrainEXE	[3] log(Y/L)	[4] TrainEXE	[5] log(Y/L)	[6] TrainEXE	[7] log(Y/L)	[8] TrainEXE
TrainEXE	0.117***		0.110***		0.122***		0.113***	
	(0.020)		(0.020)		(0.020)		(0.020)	
log(Y/L)		0.098		0.154		0.066		0.136
		(0.265)		(0.261)		(0.272)		(0.262)
Pred(OUT)		0.326**						
		(0.160)						
Pred(OUT_PROD)				0.553				
				(0.392)				
Pred(OUT_SERV)						0.296*		
						(0.152)		
Pred(OUT_JOINT)								0.297*
								(0.166)
N	1410		1410		1410		1410	
1st stage adj. R^2	0.373		0.371		0.374		0.371	
1st stage pseudo R^2	0.182		0.181		0.182		0.181	

Table 7. Second stage estimates: training of managers

	[1] log(Y/L)	[2] TrainMAN	[3] log(Y/L)	[4] TrainMAN	[5] log(Y/L)	[6] TrainMAN	[7] log(Y/L)	[8] TrainMAN
TrainMAN	0.111***		0.103***		0.116***		0.106***	
	(0.019)		(0.019)		(0.019)		(0.019)	
log(Y/L)		0.185		0.252		0.148		0.231
		(0.267)		(0.264)		(0.274)		(0.264)
Pred(OUT)		0.414**						
		(0.161)						
Pred(OUT_PROD)				0.769*				
				(0.396)				
Pred(OUT_SERV)						0.373**		
						(0.154)		
Pred(OUT_JOINT)								0.354**
								(0.168)
N	1410		1410		1410		1410	
1st stage adj. R^2	0.373		0.370		0.375		0.371	
1st stage pseudo R^2	0.199		0.197		0.199		0.197	

Table 8. Second stage estimates: off-the-job training

	[1] log(Y/L)	[2] TrainOFF	[3] log(Y/L)	[4] TrainOFF	[5] log(Y/L)	[6] TrainOFF	[7] log(Y/L)	[8] TrainOFF
TrainOFF	0.174***		0.142***		0.195***		0.162***	
	(0.027)		(0.030)		(0.033)		(0.032)	
log(Y/L)		0.361		0.447*		0.323		0.418
		(0.261)		(0.258)		(0.268)		(0.258)
Pred(OUT)		0.596***						
		(0.155)						
Pred(OUT_PROD)				1.409***				
				(0.380)				
Pred(OUT_SERV)						0.504***		
						(0.147)		
Pred(OUT_JOINT)								0.514***
								(0.160)
N	1410		1410		1410		1410	
1st stage adj. R^2	0.373		0.367		0.378		0.370	
1st stage pseudo R^2	0.111		0.110		0.111		0.108	

Table 9. Second stage estimates: on-the-job training

	[1] log(Y/L)	[2] TrainON	[3] log(Y/L)	[4] TrainON	[5] log(Y/L)	[6] TrainON	[7] log(Y/L)	[8] TrainON
TrainON	0.151***		0.142***		0.164***		0.137***	
	(0.028)		(0.029)		(0.029)		(0.027)	
log(Y/L)		0.606		0.666**		0.323		0.418
		(0.307)		(0.303)		(0.268)		(0.258)
Pred(OUT)		0.459***						
		(0.174)						
Pred(OUT_PROD)				0.689				
				(0.436)				
Pred(OUT_SERV)						0.399**		
						(0.167)		
Pred(OUT_JOINT)								0.548***
								(0.179)
N	1410		1410		1410		1410	
1st stage adj. R^2	0.373		0.369		0.376		0.370	
1st stage pseudo R^2	0.118		0.113		0.119		0.119	

APPENDIX 1

Two-stage probit least squares

The following discussion of the two-stage probit least squares model is taken from Keshk's (2003) explanation of the *cdsimeq* command for Stata.

The starting point is the following simultaneous equation model:

$$y_1 = \gamma_1 y_2^* + \boldsymbol{\beta}_1' \mathbf{X}_1 + \varepsilon_1 \qquad [A1]$$

$$y_2 = \gamma_2 y_1^* + \boldsymbol{\beta}_2' \mathbf{X}_2 + \varepsilon_2 \qquad [A2]$$

where y_1 and y_2 respectively are continuous and binary endogenous variables (the latter is observed only if the latent $y_2^* > 0$, and 0 otherwise), $\mathbf{X_1}$ and $\mathbf{X_2}$ are two matrices of the exogenous covariates, $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are vectors of the parameters, γ_1 and γ_2 are the parameters of the endogenous variables, and ε_1 and ε_2 are the two error components in A1 and A2.

Since the latent variable y_2^* is not observable, the two structural equations A1 and A2 can be written as follows:

$$y_1 = \gamma_1 \sigma_2 y_2^{**} + \boldsymbol{\beta}_1' \mathbf{X}_1 + \varepsilon_1 \qquad [A3]$$

$$y_2^{**} = \frac{\gamma_2}{\sigma_2} y_1 + \frac{\boldsymbol{\beta}_2'}{\sigma_2} \mathbf{X}_2 + \frac{\varepsilon_2}{\sigma_2} \qquad [A4].$$

In the following step, the usual two-stage approach can be applied to estimates of equations A3 and A4. In the first stage, the following two models are fitted using all the exogenous covariates in A3 and A4:

$$y_1 = \mathbf{\Pi}_1'\mathbf{X} + u_1 \quad \text{[A5]}$$

$$y_2 = \mathbf{\Pi}_2'\mathbf{X} + u_2 \quad \text{[A6]}$$

where **X** is a matrix including all the exogenous covariates, $\mathbf{\Pi_1}$ and $\mathbf{\Pi_2}$ are vectors of parameters to be estimated, and u_1 and u_2 are the error terms. Equation A5 is estimated via OLS, and equation A6 via probit. Then, the predicted values for each model are obtained for use in the second stage: $\hat{y}_1 = \hat{\mathbf{\Pi}}_\mathbf{1}\mathbf{X}$ and $\hat{y}_2^{**} = \hat{\mathbf{\Pi}}_{12}\mathbf{X}$.

In the second stage, the original endogenous variables in A3 and A4 are replaced by their predicted values, and re-estimated via OLS and probit respectively. The last step is the computation of corrected standard errors since in the second-stage estimation the standard errors are obtained using the predicted values of y_1 and y^{**} and not their observed values.

The process for correcting the variance-covariance matrix is based on the program described by Amemiya (1978) and Maddala (1983), and is developed using standard built-in Stata procedures explained in detail in Keshk (2003).

APPENDIX

Table A1. Robustness check: first-stage bivariate probit estimates

	[1] Only Product	[2] Only Service	[3] Product	[4] Service	[5] Both
Uncertainty	0.005	0.005	0.010**	0.009*	0.004**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)
North West	0.119***	-0.030	0.152***	0.003	0.033**
	(0.040)	(0.027)	(0.050)	(0.037)	(0.016)
North East	0.126***	-0.015	0.170***	0.029	0.045**
	(0.047)	(0.031)	(0.058)	(0.044)	(0.020)
Centre	0.125**	-0.027	0.158**	0.007	0.036
	(0.060)	(0.029)	(0.072)	(0.045)	(0.022)
South	Ref.	Ref.	Ref.	Ref.	Ref.
District Region	-0.037	0.014	0.004	-0.058	-0.010
	(0.039)	(0.029)	(0.050)	(0.065)	(0.017)
Small	0.069**	-0.044***	0.072**	-0.042*	0.003
	(0.028)	(0.017)	(0.033)	(0.024)	(0.010)
Medium	0.025	-0.044**	0.019	-0.050**	-0.006
	(0.016)	(0.016)	(0.028)	(0.021)	(0.008)
Large	Ref.	Ref.	Ref.	Ref.	Ref.
ULC	-0.026	0.017	-0.031	0.013	-0.004
	(0.020)	(0.021)	(0.027)	(0.029)	(0.010)
R&D	0.001	0.006***	0.004*	0.009***	0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
M&E	0.002	0.007***	0.005**	0.010***	0.003***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.000)
N			1410		
ρ			0.425***		

Notes: cells in Columns 1and 2 report marginal effects on the (marginal) probability to outsource, respectively, only production and only service activities. Cells in Columns 3 and 4 report marginal effects on the probability to outsource production and service activities. Cells in Column 5 report marginal effects on the joint probability to outsource both production and service activities.

Table A2. Robustness check: second-stage estimates with observed outsourcing

	[1] log(Y/L)	[2] Training	[3] log(Y/L)	[4] Training	[5] log(Y/L)	[6] Training	[7] Log(Y/L)	[8] Training
Training	0.126***		0.109***		0.138***		0.120***	
	(0.021)		(0.021)		(0.022)		(0.022)	
log(Y/L)		0.382		0.471**		0.357		0.467*
		(0.257)		(0.256)		(0.266)		(0.257)
log(K/L)	0.152***		0.155***		0.150***		0.154***	
	(0.013)		(0.013)		(0.013)		(0.013)	
$\log(L^H/L)$	0.290**	0.979**	0.291**	1.095**	0.270**	0.968**	0.270**	0.996**
	(0.125)	(0.438)	(0.121)	(0.436)	(0.127)	(0.439)	(0.123)	(0.441)
$\log(L^U/L)$	-0.652***	0.343	-0.660***	0.390	-0.652***	0.360	-0.660***	0.413
	(0.118)	(0.437)	(0.114)	(0.433)	(0.120)	(0.442)	(0.116)	(0.439)
Export	-0.015		-0.009		-0.019		-0.013	
	(0.030)		(0.029)		(0.031)		(0.030)	
Pred(OUT)		0.527***						
		(0.162)						
OUT	-0.073							
	(0.060)							
Pred(OUT_PROD)				1.216***				
				(0.394)				
OUT_PROD			-0.079					
			(0.0629					
Pred(OUT_SERV)						0.439***		
						(0.153)		
OUT_SERV					-0.069			
					(0.050)			
Pred(OUT_JOINT)								0.448***
								(0.168)
OUT_JOINT							-0.102	
							(0.076)	
Industry dummies	Yes		Yes		Yes		Yes	
Size dummies	Yes		Yes		Yes		Yes	
Area dummies	Yes		Yes		Yes		Yes	
N	1410		1410		1410		1410	
1st stage adj. R^2	0.376		0.371		0.377		0.371	
1st stage pseudo R^2	0.166		0.164		0.166		0.164	