Production offshoring and the skill composition of Italian manufacturing firms
A quasi-experimental analysis

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Abstract

This work explores the effects of production offshoring on the workforce skill composition of manufacturing firms. Its aim is to assess if the firms' strategy to offshore production activities determines a bias in the in-house employment of labor in favour of high-skilled workers. Using three repeated cross-sections of firm-level data over the period 1995-2003, we employ a non-parametric analysis based on propensity score matching thanks to which we can control for selectivity bias without relying on a specific functional form of the relations of interest. We test the effect of production offshoring on the workforce skill composition of manufacturing firms by employing different measures of skills by occupational title. Our results point to a weak, but down-skilling, impact of delocalization on the labor composition of Italian manufacturing: in particular, we find that firms that farmed out production activities in 1998-2000 generally employ a lower share of skilled, non manual, workers with respect to the counterfactual of non-delocalizing firms. These results seem to be in line with an idea of defensive offshoring. However, despite the usual findings that mainly stress the negative impact of delocalization on low-skilled workers, we find here that middle-managers category is the most affected. Such evidence may find a twofold explanation: on the one hand, skilled workers can decline more than unskilled workers because of a substitution effect that is driven by the will of reducing not only redundant activities, but also intermediate skills-intensive activities as control and coordination for which middle-managers are employed for. On the other hand, skilled workers may decline in absolute terms, because of a quantity effect that occurs when firms decide to transfer managerial staff in order to coordinate and supervise the activities shifted abroad.

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1. Introduction

During the last three decades the way goods are manufactured has dramatically changed. Next to an extensive use of IT capital, imported materials, intermediate services and skilled labor, an increasing replacement of low-skill employment is occurring due to the fact that firms de-locate low-skill intensive activities towards less developed, cheap labor, countries. Trade flows, import competition and foreign direct investments (FDI), thus, result in a reorganization of production in which home firms can specialize on the high-value-added phases of production while economizing on production costs.

Traditionally, two main explanations have been given to account for the shift in demand away from low-skilled workers in industrialized countries. The first refers to skill-biased labor-saving technological change that, by fostering the demand for more qualified workers within technologically advanced industries, tends either to increase the wage inequality in relatively flexible labor markets (like in the US and in the UK) or to increase relative unemployment of less qualified workers in relatively more rigid labor markets (as in Germany, France, Denmark and Italy)[3].

The second claims for increased international trade and globalization, according to which labor is relocated in a way that determines a shift of activities involving unskilled workers toward less-developed countries, while keeping activities typically developed by high-skilled workers within industrialized countries, thus increasing their comparative advantage in the production of high-skill intensive goods.

On this field, neoclassical trade theory asserts that increased import competition from low-wage countries plays a minor role in explaining the causes of the deterioration in the economic fortunes of less-skilled workers. According to the Hecksher-Olin-Samuelson (HOS) model, an increase in the volume of foreign trade should simultaneously lead to a convergence in wages between the home and the host country and a widening in the gap between wages of low-skilled and

3 For a review of theoretical and empirical models of skill-biased technological change see Chennels and Van Reenen (2002), Piva (2004) and Antonietti (2007).

high-skilled employees within the home country. Thus, a decrease in the wage rate of low-skilled workers should stimulate firms to increase the demand for this now cheaper factor. However, the observed deterioration in the economic fortunes of less-skilled workers seems to be at odds with these predictions, so that the help of empirical analyses is needed.

In the last two decades, different attempts have been made in order to empirically prove the skill-biased nature of international fragmentation. On the one hand, some studies support traditional theories of international trade concluding that import competition is not an important determinant of relative wage or employment shares, especially if compared to labor-saving technological change. On the other hand, however, some studies argue that increased import intensity exerts a negative impact on both the employment and the wage share of less qualified workers.

Finally, a recent strand of industrial economics literature have stressed the importance that the objectives underlying the decision to offshore production have in generating occupational effects on the home country's labor force. Production delocalization characterized by a *defensive* nature, primarily aimed at increasing the firms' competitiveness through a labor costs-saving strategy, by shifting away of routine activities tends to reduce both the employment of production and the employment of non-production workers. When production delocalization is, on the other hand, pushed by the will to search for new market opportunities or specific competencies not directly available at home, a virtuous cycle in favour of the employment of highly qualified human resources may occur, based on the fact that, when externalizing redundant stages, the firm can rely on its high-value added activities and exploit its core competencies.

Our contribution to the debate moves in two directions. First, we focus on a sample of manufacturing firms located in Italy, a country that has received little attention in empirical studies, but that, due to its structural characteristics and to its recent intensive activity in international delocalization, represents an interesting laboratory for testing the labor market effects of production offshoring. Second, we employ a non-parametric approach, based on propensity score matching, in order to test the skill-bias effect of production offshoring avoiding any selectivity bias and without estimating specific functional forms of the objective functions.

The article is structured as follow. Section 2 briefly sketches the empirical literature developed around skill-biased international fragmentation. Section 3 describes data and the empirical methodology adopted in the analysis. Section 4 presents and discusses the main results achieved and Section 5 concludes.

2. Background literature

The labor market effects of production globalization have often been a ‘hot topic’ for both international trade and labor economists. According to Jones and Kierzkowski (2001), international fragmentation can be thought as a process of splitting up and spread of previously integrated stages of production over an international network of production sites. More specifically, production offshoring refers to the de-localization of manufacturing activities towards a low-cost country or region. To the extent that this practice determines a reorganization of the production process, it implies a labor recomposition within offshoring firms,

This paper basically links two strands of empirical literature: works looking at the determinants of the firms’ offshoring decision and works investigating the effects of such a decision on the labor composition of the manufacturing firms.

With respect to the determinants, standard theory and evidence generally suggest two factors as responsible for the choice to re-locate production outside the firm’s boundaries (Abraham and Taylor, 1996; Grossman and Helpman, 2002; Antràs and Helpman, 2004; Girma and Görg, 2004). The most important refers to the possibility to save on labor costs, that is, to cut wage and benefit costs for non-core employees by farming out peripheral stages of production towards low-wage countries. On this purpose, high-wage firms are typically expected to offshore production more intensively than low-wage firms.

A second factor is the search for specialized skills and equipment that the firm lacks at home. What is relevant here is the presence of scale economies in the provision of the production or service in question. In fact, there may be scale economies in the production of specific inputs and, in this sense, firm size becomes a determinant of its delocation strategy: since small and medium firms usually have more difficulties to reap the minimum efficient scale, they are more willing to externalize production. However, as small firms are less flexible than large firms in adapting to consumers demand variability, or as they can face higher search costs, a positive relationship may also emerge between firm size and offshoring.

In addition, next to labor cost savings and the seek for economies of scale, other factors may contribute to affect firm's decision to farm out production. Görg and Hanley (2004), for instance, point that export propensity may have a positive effect on production offshoring: the more a firm exports, the more the possibilities to find foreign low wage suppliers. Technology also can represent an important determinant (Tomiura, 2004; Bartel, Lach and Sicherman, 2005): in particular, a positive relation can be thought between offshoring and an intensive use of computers at the workplace, a high R&D intensity, or the presence of a highly skilled workforce within domestic firms. In addition, firms closer to the technological frontier are supposed to be more willing to decentralize their activities in order to deal with information not directly available in the public history (Acemoglu *et al.*, 2006).

With respect to the labor market effects, industrial organization literature have emphasized the importance of considering the strategic reasons underlying the firms' decision to offshore production. If offshoring is primarily driven by the seek for new markets and new competencies, the impact on the home country employment may be neutral or even positive, especially for high-skilled workers. If, on the other side, offshoring is driven by a 'defensive' behaviour aimed at increasing the firm's price competitiveness by cutting production costs, then the impact on home employment may be negative, in particular for low-skilled workers.

The evidence available from international trade literature, however, does not seem to depict a clear-cut framework. A first class of empirical studies is in line with HOS predictions in not finding a clear positive relationship between offshoring, declined as import competition, and the rise in the demand for skilled relative to unskilled labor, whereas a second, relatively more recent, class does find, in particular, a significant and negative impact of import competition, or international outsourcing, on the relative employment and wages of unskilled workers in industrialized countries.

Within the former group, the general emerging result is that technological change, rather than increased import competition, is the major responsible of the declining economic fortunes of low-skilled workers. The first set of contributions on this field develops around the late 1970s, and, looking at the US and UK product and labor markets, generally finds that import competition is a minor factor in explaining labor displacement if compared to other structural changes (Cable, 1977; Krueger, 1980a, 1980b). On the same line, even if decomposing the separate effects on employment and wages, Grossman (1987) finds that import competition is responsible for the loss of a large number of jobs only in one industry over nine, and for the decline in wages only in two industries.

During the 1990s, other studies improve the measurement of import competition and compare this variable with proxies of technological change, but still provide a weak evidence on the trade-skill complementarity hypothesis. For the US, Freeman and Katz (1991) find, on the one side, a significant effect of import competition on the employment composition in the steel industry over the period between 1976 and 1983, but, on the other, they find a small correlation between volumes of imports and changes in real wages. Katz and Murphy (1992), using individual and labor market data between 1963 and 1987, find that outsourcing, i.e. shifts of portions of industry production outside the United States, is not an important determinant of relative wage changes. Lawrence and Slaughter (1993), looking at the effects of trade on the US average performance and wages in the 1980s, do not find support for the idea that import competition places downward pressure of relative wages of unskilled workers. On the same line are Berman *et al.* (1994), who, estimating trans-logarithmic labor demand equations, obtain only a small employment effect of increased import competition with respect to production-labor-saving technological change. More recently, Slaughter (2000) analyzes 32 US manufacturing industries in the 1980s and does not show clear results in favour of the positive relationship between FDI and the employment of skilled workers at home. Finally, Morrison-Paul and Siegel (2001), using a dynamic cost function framework, find that technological change still exerts the largest effects on changes in domestic labor composition, while international trade, by stimulating the adoption of computers at the workplace, tends only to augment the skill-bias effect of technology.

Evidence against the skill-bias effects of import competition and outsourcing comes also from studies on European countries. For the UK, for instance, Görg *et al.* (2001), focusing on the increasing trade in intermediate goods in the 1982-1996 period, find weak or no evidence of a positive relationship between outsourcing and wage inequality. For Germany, Fitzenberger (1999) leaves a dominant role for technology in shifting unskilled employment away, while Falk and Koebel (2000), estimating a Box-Cox cost function, provide no evidence for skill-bias service outsourcing, even if they recognize a significant substitution effect between high-skilled labor and intermediate services. Finally, a low significant impact of FDI on the skill employment ratio is found by Piva and Vivarelli (2004) for the case of Italian manufacturing firms in the 1990s, even if the nature of the data do not allow the *a priori* exclusion of a possible interaction.

Contrary to this strand of literature, another set of contributions provide general support for the skill-biased nature of international trade. For the US, Revenga (1992) analyzes import price data on a panel of manufacturing industries and finds that the dollar appreciation occurred during the 1980s is at the basis of the significant and sizable negative effect of increased import competition and both employment and wages, even if results concern between industries, rather than within industries, effects. Wood (1994), in addition, finds a general skill-biased impact of international trade and calculates that import competition determines a reduction in the demand for unskilled labor by 30% in 1990. On the same line are Sachs and Shatz (1994), who conclude that production internationalization exerts a double effect on overall labor composition: it is not only the cause of a general decrease in manufacturing but, together with technological change, is a determinant of the decline in the relative demand for low-skilled workers. Moreover, Feenstra and Hanson (1996) give some evidence that, for the period 1972-1990, international outsourcing is responsible of a 30% to 50% rise in the demand for skilled workers, and, thus, for a rise in income inequality.

For the UK, Anderton and Brenton (1999) estimate that, between 1970 and 1986, imports from low-wage countries determine a negative impact of about 40% on the wage-bill share and relative employment of low-skilled workers. This result is further reinforced by Hijzen *et al.* (2004), who show that, between 1982 and 1996, international outsourcing has a strong negative impact on the demand for semi-skilled and unskilled labor.

For France, Strauss-Khan (2003), using input-output tables and labor data, finds that the highly increasing vertical specialization, i.e. the share of imported inputs in production, is the main determinant of the sharp decline in the share of unskilled workers between 1977 and 1993, passed from -15% in the period 1977-85 to -25% between 1985 and 1993.

Finally, a mixed picture emerges from other studies that control for different measures of import competition and compare different countries. Looking at Japanese manufacturing firms, for instance, Head and Ries (2002) find that a positive relationship between outsourcing and the employment of skilled labor holds only if the former turns towards developing countries. For Austria, instead, a positive and significant effect on skills comes out only for proxies of international trade like export openness and outsourcing, while a negative effect arises when considering import penetration (Dell'mour *et al.,* 2000). Finally, Helg and Tajoli (2005) compare the effect of international fragmentation of production on the skill ratio in Italy and in Germany and show that a positive and significant impact emerges only for the former, while for the latter a negative effect seems to prevail.

Concluding, the most recent literature on skill-bias international fragmentation of production seems to generally stress the negative impact of production offshoring on the employment and pay of unskilled relative to skilled workers. However, what also emerges is that country specific effects, different econometric techniques and different measurements, of both international fragmentation and labor skills, as well as different time periods matter in explaining such a variety of effects.

In this respect, Kohler (2001) and Egger and Egger (2001) summarize the ambiguity with the idea that the income and employment effects of international fragmentation depend on the factor intensity assumptions for the outsourced and non-outsourced production phase together with the skill intensity of the outsourcing industry. Foreign investments in low-income countries, relatively abundant of unskilled workers, should consist in the move away of low-skill intensive stages of production, thus causing a skill upgrading within high-income countries. On the other hand, a skill downgrading process should emerge if production delocalization involves investments in high-income countries, that are supposed to be relatively abundant of high-skilled labor.

Whether international delocalization is a sufficiently large phenomenon in order to account for any economically significant labor market effects is, therefore, an empirical matter.

3. Methodology and data

Empirical works testing for the skill-biased international trade are generally based on the estimation of labour demand equations, typically in a transcendental logarithmic form (Berman *et al.*, 1994). However useful, this approach suffers some limitations. First of all, it relies on a simple cost or production function framework, which is subject to a set of *ad hoc* restrictions in order to assure its tractability: optimization restrictions (Christensen *et al.*, 1973), homogeneity assumptions (Morrison-Paul and Siegel, 2001) and the specific parametric form that constraints the parameters to assume specific values. Second, limited information is usually provided on labour composition and firms characteristics, these latter being particularly important if one believes that firms endogenously choose to invest abroad by looking at previous experience and at the composition of its internal assets. Thus, a possible problem of self-selection may arise, according to which the set of firms which decide to transfer production stages abroad cannot be thought as a randomly drawn sample.

3.1. The evaluation problem and the Propensity Score Matching (PSM)

Our main empirical contribution to the debate is to bypass the issues above by employing a non-parametric approach based on PSM (Rosenbaum and Rubin, 1983) developed within the evaluation literature in a context of observational data (Angrist, Imbens and Rubin, 1996; Heckman, 1990, 1997; Heckman, Hichimura and Todd, 1997; Heckman, LaLonde and Smith, 1999; Sianesi, 2004; Wooldridge 2001; Smith and Todd, 2005). On this purpose, PSM is a more flexible technique with respect to standard labour demand estimation, because it does not force the imposition of a parametric specification and it allows to handle the selection bias along with the problem of (time-invariant) unobserved heterogeneity when the outcome variable is appropriately constructed by exploiting the repeated cross section structure of the data.

In what follows we make explicit at first the evaluation problem and then the assumptions on which the PSM relies on.

The evaluation refers to a process aiming to assess (or infer) the effect of a treatment administered to a subset of individuals (participants) within a population on an outcome variable. Ideally such effect ought to be found comparing the outcomes of the same individuals in the case they receive the treatment and in the case they do not receive the treatment[4]. However, the latter it is obviously not a viable option: individuals cannot be simultaneously participants and not participants, they are in one state or another at a point in time. For such a reason the evaluation problem is essentially a missing data problem.

In order to describe a general formulation of the parameter of interest in this work let assume we have a binary treatment variable so that we can denote treated individuals by D=1 and not treated by D=0. Associated with the two states

4 In the work we use participation (participant) and treatment (treated) as synonymous throughout.

we have two outcomes: Y_1 and Y_0 .

The effect of interest is the gain from treatment:

$$\Delta = Y_1 - Y_0 \quad .$$

One specific definition of such a gain, which is the main parameter of interest in a wide part of the evaluation literature, is the Average Treatment Effect on the Treated (ATT):

$$ATT = E(\Delta | X, D=1) = E(Y_1 - Y_0 | X, D=1) = E(Y_1 | X, D=1) - E(Y_0 | X, D=1)$$

where X is a vector of observed conditioning variables. What we lack in order to directly compute the ATT is the counterfactual outcome $E(Y_0 \mid X, D=1)$: that associated to the state D=0 for treated individuals, which are obviously in the state D=1. Within non experimental, or observational, frameworks we need to find a proxy of the mean counterfactual (Smith and Todd, 2005). The difference between the proxy and the ideal mean counterfactual represents the selection bias or evaluation bias that "arises because participants and non participants are selected groups that would have different outcomes, even in absence of the [treatment]" (Caliendo and Hujer 2005, p. 4).

As stated above, we decide to implement the PSM to solve the problem of the missing counterfactual. The rationale for PSM implementation is grounded on the plausibility of the Conditional Independence Assumption (CIA), which is an identification assumption, that can be formalized as follows[5] (Heckman, Ichimura, Todd 1997, 1998; Smith and Todd 2005):

$$E(Y_0 | X, D=1) = E(Y_0 | D=0) = E(Y_0 | X) \qquad \text{(A1)}$$

Moreover, the computation of the ATT through the PSM needs the validity of the assumption that a positive probability of participating (D=1) exists:

5 For a more restrictive condition when the parameter of interest is not the ATT see Rosenbaum and Rubin (1983).

$$pr(D=1|X)>1 \qquad \text{(A2)}$$

where $pr(D=1|X)$ is the propensity score, that is the probability of being a treated individual given a certain vector X of exogenous characteristics. Roughly speaking, A1 means that the available variables are all those on which the decision of participating is based on or, put it another way, that there are not unobservable variables that influence the participation decision. A2, instead, is a condition that guarantees the existence of a non participant analogue of the treated individuals, so that we need to have a counterfactual individual for each treated individual (Smith and Todd 2005; Heckman, Ichimura, Smith and Todd, 1998). If A2 is not verified, then the support of participant is not equal to that of controls: the support of X does not overlap[6] for treated and non treated. In such a case as Heckman, Ichimura and Todd (1997), Heckman, Ichimura, Smith and Todd (1998) and Dejha and Waba (1999) put forth the estimation of the ATT must be conducted over the common support region, discarding observations that lie outside the common support, and the "estimated treatment effect must then be redefined as the treatment impact for the […] participants whose propensity scores lie within the common support region" (Smith and Todd 2005, p.313).

The use of propensity score as a device to find appropriate matches for treated individuals was introduced by Rosenbaum and Rubin (1983), who demonstrated that if CIA holds then the PSM gives unbiased estimate of the ATT. The construction of a counterfactual sample[7] of non treated individuals that share the same pre-treatment characteristics of the treated individuals comparing each observed variable of the vector X (i.e. multivariate matching) represents a data-hungry process if the characteristics on which the counterfactual is constructed are in a large number. In order to solve the high dimensionality problem Rosenbaum and Rubin (1983) proposed to utilize the propensity score to reduce the multidimensional matching to a one dimensional procedure. If the propensity

6 In the microeconometric evaluation literature A2 is often called *overlapping* assumption.

7 Rubin (1979) demonstrates that in order to reduce the selection bias as much as possible it is necessary to have a large reservoir from which select the counterfactual sample. The larger is the reservoir the greater is the reduction in bias obtainable through the matching.

score satisfies the balancing property, about that we give more details below, then we can condition on it instead of the vector X and A1 becomes (Smith and Todd 2005):

$$E(Y_0 | pr(X), D=1) = E(Y_0 | pr(X), D=0) = E(Y_0 | pr(X)) \qquad (\mathrm{A1^I})$$

When using the PSM the estimated ATT may be affected by a bias due to unobserved heterogeneity. If unobservable variables exist and they influence the participation decision or the outcome then the CIA assumption does not hold anymore. One approach to handle the problem of unobserved heterogeneity consists in combining the Difference-In-Differences (DID henceforth) estimator with the PSM. The mix of the two estimators can help in reducing the bias due to unobservable time invariant individual characteristics (Blundell and Costa Dias 2004; Smith and Todd 2005; Heckman, Ichimura, Smith and Todd 1998)[8]. The implementation of the DID estimator is subjected to the availability of data in a longitudinal or repeated cross-section format.

3.2. Implementation

Operationally, the Difference-In-Differences-Propensity Score Matching (DID-PSM henceforth) approach we implement in this work consists in a two step procedure. For our purpose, we estimate, at first, the probability of being a delocalizing firm (the propensity score) conditional on the vector of firm characteristics *X*. These variables are supposed not only to affect the firm's decision to offshore production, but also to have an influence on the dependent variable, i.e. the skill composition of the labor-force. In this respect, we consider a set of controls on firm's geographical location, sector[9] of economic activity, size,

8 However useful the DID-PSM procedure is not formulated to specifically solve the problem of unobserved heterogeneity. The existence of heterogeneity not observed by the researcher that invalidate the CIA assumption is one of the dominant issues in the recent evaluation literature. In order to test how sensible is the estimated ATT with matching procedure to the presence of unobserved heterogeneity a sensitivity analysis is recommended. Here is a list of some recent contributions on this issue: DiPrete and Gangl (2004); Ichino, Mealli and Nannicini (2006); Nannicini (2007); Caliendo and Becker (2007).

9 We use the Pavitt taxonomy instead of a standard ATECO classification of economic sectors in

age, the possibility to be a member of a group of firms and the possibility to have broken up in sub-units. Since the delocalization decision could have been taken in each one of the years belonging to the triennium 1998-2000, we believe that also firm characteristics collected on such a triennium might have influenced the decision to offshore production as well[10]. Following standard empirical literature on international fragmentation, we also included variables capturing firm's international activity - represented by a FDI dummy - firm's technology - given by a R&D dummy - labor cost per employee, firm's average productivity and the capital intensity of the production process, these latter approximating the complexity of the production process. Finally we included a variable of financial profitability represented by returns on investments (for a description of the variables see Table A1 in the Appendix).

At the second stage, we use the propensity score obtained to estimate the ATT. In our case the outcome variables are the DID in levels of the skill ratios of the workforce and the DID in levels of employees decomposed in occupational categories (managers, middle managers, clerks and manual workers, see Table A2 in the Appendix)

In the first stage, the estimation of the probabilities is conducted by means of a probit specification, which gives as coefficients the estimated probabilities of cross-border delocalization. The fitted values of the binary model are then used in order to correctly align the units on their common characteristics and the mean comparison in the second stage is performed on the counterfactual units so aligned, that is on the units lying over the common support.

Since we adopt a probit specification, the propensity score can be written as follows:

$$\hat{P}_i = Pr\left(Deloc_{1998-2000} = 1 | X_i\right) = \Phi\left(\hat{\beta} X_{i,1995-97;1998-2000}\right)$$

order to avoid the possibility of perfect identification of the sample during the estimation.

10 LR test confirms that, not including variables in the latter period would bring to a joint non-significance of all the covariates.

where X is the vector of pre-treatment (and contemporaneous to treatment) observed variables that, in line with the literature, we consider as determinants of delocalization (and possibly influencing also the outcome variables), an Φ is the standard normal cumulative distribution function. Thus, the estimated probability $\hat{P}_i$ is the propensity score for each firm.

At this stage, a first issue we need to address is the balancing property of the propensity score[11]. In order to test for it, we implement the procedure developed by Becker and Ichino (2002), according to which, if the balancing property is satisfied, than exposure to treatment is random, so that the decision of delocalization becomes random as well[12].

In the second stage of the estimation we apply the DID-PSM. In order to implement it we need to choose the algorithm to be used in the construction of the weights $W(i, j)$, where i and j identifies respectively a treated and non treated firm, that are necessary to assign to the counterfactual firms in computing the ATT (Caliendo, Hujer and Thomsen, 2005). The specific construction of the weights depend on the propensity score and on the kind of matching (algorithm) used (nearest neighbour, kernel, radius, and so on).

We decide to implement the nearest neighbour (NN from now on) algorithm with two specifications. Since NN matching pairs each treated firm to one counterfactual firm, the closest neighbour of the treated unit, it likely minimizes the bias at the expenses of the efficiency. Usually a trade-off between variance and bias arises when applying one or the other of the available algorithms for the matching estimation. In our case, in order to reduce the loss in efficiency that NN bears on we also use an oversampling version of the NN. In so doing we allow the

11 It must be noted that there is no agreement in the literature about the choice of the observed variables to be introduced in the binary model. On the one hand in order to have the counterfactual units as similar as possible to the treated ones we should use all the observed variable at our disposal: the more are the firms characteristics on which we condition the probability of participation the more precise will be the matching between treated and counterfactual units. On the other hand, this way of proceeding has a drawback because the more observed variables are included in the specification the more difficult will be to find a common support and it can also increase the variance of the estimates (Rubin and Thomas 1996; Caliendo, Hujer and Thomsen 2005).

12 See Becker and Ichino (2002) for a detailed description of the procedure for testing the balancing property.

comparison of each treated unit to more than a single closest counterfactual unit (Smith, Todd 2005; Caliendo, Hujer, Thomsen 2005).

Finally, the ATT is then computed in the following way:

$$\widehat{ATT} = \frac{1}{N_t} \sum_{i=1}^{N_t} (Y_i^t - \sum_{j=1}^{N_t} W(i, j) Y_j^c)$$

where N_t is the number of delocalizing firms. Operationally the standard errors of the $\widehat{ATT}$ are generated by bootstrapping.

In conclusion, the main aim of the DID-PSM score matching method is to generate a set of non delocalizing firms, among all those that do not delocalize, as more as similar to the delocalizing firms in order to get a “proxy” of what would have happened to domestic skill composition in actually delocalizing firms they had not chosen to displaced activities outside national borders. Thus, to gather an estimate of the skill-biased nature of international fragmentation, once we obtain adequate control groups for firms offshoring production to less developed-low labour cost countries, we compare their pattern of skilled labour employment with the one of the actually delocalizing firms.

3.3. Hypotheses

We formulate and test two hypotheses about the effects of production offshoring on the skill intensity of manufacturing firms in Italy.

H1. *Production offshoring alters the scale of activity of home firms, thus exerting a negative impact on employment. If this is the case, it can generate either (H1.1) a skill-biased effect by decreasing more the share of unskilled relative to skilled workers, or (H1.2) a skill downgrading pattern by decreasing more the share of skilled workers per unit of unskilled workers.*

H2. *Production offshoring consists in the mere replication of all, or part, of domestic activities. In this case the effect on the skill composition can be neutral,* *if the scale of activity of home firms does not change, or negative if we suppose that domestic firms transfer part of their managerial skills to foreign sites.*

Hypothesis H1 may reflect two possible scenarios that can characterize the strategy of internationalization of manufacturing firms. Since the question formulated in the questionnaire is "*Has the firm delocalized its own productions in Centre-East European countries […] in the triennium 1998-2000?*", it is likely the case that offshoring firms in our sample have adopted such a strategic behaviour in order to merely reduce labour costs and improve their price competitiveness. Italian firms, which seems to base their competition on strategic reduction of production costs (Capitalia, 2001), may find an opportunity of persevering in a low-profile strategic behaviour by delocalizing part of their production in markets where manual workers are paid less than in the domestic labour market. If this is the case, then the likely effect should be an overall reduction in the domestic employment, even if the source of such a decrease can be twofold: (i) a higher reduction in the share of production workers (blue-collars) relative to non-production (white-collars), but also (ii) a possible higher reduction in the relative share of non-production workers with respect to the reduction in the share of production workers.

Hypothesis H2, instead, reflects the possibility that production offshoring may be a horizontal investment, that can either reduce the scale of domestic activity- because of a relocation of redundant processes – or leave it unaltered if we suppose that foreign activities are independent from domestic ones.

3.4. Data

We test these predictions on a sample of Italian manufacturing firms taken from the last three waves (VII, VIII and IX) of the Survey on Manufacturing Firms (*Indagine sulle Imprese Manifatturiere*) conducted by Capitalia (ex Mediocredito Centrale) and covering the period 1995-2003. For the three surveys, interviews have been respectively conducted in 1998, 2001 and 2004 over all firms with more than 500 employees and over a representative sample of firms with more than 11 and less than 500 employees, stratified by geographical area, sector of economic activity and size. In our analysis we use a panel of firms appearing in all three waves, 1995-97, 1998-2000 and 2001-03. Each of the three waves gather information on 4.497, 4.680 and 4.289 firms respectively, while the number of firms we obtain from merging the three cross-sections is 414 that, after further cleaning (for our purposed estimation), decreases to 330.

As it can be noted in the Table 1 below, the majority of the firms in our restricted sample is constituted by small and medium small firms (74,5%). Supplier dominated and specialized suppliers firms represent the only sectors out of four having experienced production offshoring[13], so that firms belonging to scale intensive and science based sectors have been *ex ante* eliminated in order to avoid the generation of bad matches[14].

Table 1. Sample structure by economic sector and employment size

Size	**Supplier Dominated**	**Specialized Suppliers**	**Total**
11-20	30	11	41
21-50	68	52	120
51-250	72	54	126
251-500	15	10	25
501+	9	9	18
Total	194	136	330

Source: authors elaborations from the Capitalia sample, 1995-2003.

Table 2 shows that only 18 (about 5%) of the 330 firms have chosen to offshore production. Such a figure, however, overestimates the percentage of offshoring firms in the complete Capitalia sample coming from the VIII wave of the Survey on Manufacturing Firms, which is equal to the 1.9% of the entire sample (Capitalia, 2001). Another important aspects that should be stressed is that, differently from to the original 1998-2000 cross-section – in which the share of offshoring firms progresses along with their employment size - in our merged sample small and medium firms show a higher propensity to delocalize than large

13 This is in line with Capitalia (2001) and Fortis (2005), who find that the most involved sectors in offshoring practices are textile and clothing, leather and shoes and machinery.

14 We replicated the same estimations for the whole matched sample of 414 firms without reaching different outcomes.

firms. Even if this can represent a bias of representativeness, it should be noted that our sample cleaning allows us to replicate a quasi-experiment in which we ‘isolate’ only firms that are present in each time span, located in the most active environments (sectors) with respect to the ‘treatment’ of interest, i.e. offshoring, and maintaining the general employment size distribution with respect to the original cross-sections.

Table 2. Offshoring by sector of economic activity and employment size

Offshoring	**Num. Obs.**			**Frequency**		
No	314			95.15		
Yes	16			4.85		
Total	330			100.00		
Offshoring	**Sectors of economic activity (Pavitt classification)**					**Total**
	Supplier Dominated			**Specialized Suppliers**		
No	185			129		314
Yes	9			7		16
Total	194			136		330
Offshoring	**Employment size**					
	11-20	**21-50**	**51-250**	**251-500**	**501+**	**Total**
No	39	114	122	22	17	314
Yes	2 (4.88%)	6 (5%)	4 (3.17%)	3 (12%)	1 (5.56%)	16
Total	41	120	126	25	18	330

Source: authors elaborations from the Capitalia sample, 1995-2003.

4. Estimation and results

Some first interesting observations can be drawn by looking at the trend of the variables used to construct the outcomes of the DID-PSM, for delocalizing and non delocalizing firms, along the time span 1995-2003. Figures 1A-2A in Appendix show the trends of the employment composition by skill ratios and occupational categories for firms on the common support. As far as the skill ratios are concerned, the ratio between non-manual and manual workers does not show any relevant difference in the trend along the time span considered (1995-2003).

When we shift the attention to less aggregate indicators of skill ratio, using the decomposition of occupational categories for non-manual workers (managers, mid-managers and clerks), the evidence about the trends becomes more heterogeneous and not easily interpretable. A quite sharp decline is shown by the ratio of middle-mangers on manuals and middle-managers on clerks plus manuals after the triennium of delocalization for offshoring firms. The same variables evidence also an increasing trend in the period just before the triennium in which offshoring took place. On the contrary the skill ratios of non delocalizing firms put in evidence a smother trend over the entire time span[15].

Looking at the trend of occupational categories the framework seems quite clear: while clerks and manuals do not show relevant alteration in their trends before and after the delocalization, managers and middle-managers appear to have quite abrupt shifts. The first impression leads us to expect some significant impact of offshoring on skill ratios and occupational trends involving managers and middle-managers, in line with hypothesis H1.

Before proceeding with the comments of the main results of DID-PSM it is convenient to spend some words on the determination of the propensity score and the presence of firms on common support. As stated above the procedure adopted to test for the balancing property of the propensity score is that developed by Becker and Ichino (2002). After having estimated the probability of being an offshoring firm the steps are the following (Tab.A3.1-A3.3): "*split the sample in k equally spaced intervals of the propensity score* […]; *within each interval test that the average propensity score of treated and control units do not differ; if the test fails in one interval, split the interval in halves and test again [and] continue until, in all intervals, the average propensity score of treated and control units do not differ; within each interval, test that the means of each characteristic do not differ between treated and control units*" (Becker and Ichino, 2002, p.3).
If the balancing hypothesis was not satisfied then the researcher ought to find a new and less parsimonious specification of the binary model. The balancing property in our case is satisfied[16].

As far as the distribution of the firms on the common support is concerned, Fig.A3 and Tab.A3.3 show that two delocalizing firms are not on the overlapping

15 To this results contributes quite heavily the number of firms in the two groups on the common support: 16 at maximum for delocalizing firms; 104 for non delocalizing firms.

16 The output of the Becker and Ichino (2002) module is not fully reported but it is available upon request.

support. This means that in the matching estimation two treated units don not have appropriate counterfactual units and they cannot enter in the comparison procedure. The information of such units is lost. Discarding two delocalizing firms out of sixteen it might conduce to misleading interpretations, thus, among other things, we have to be careful in interpreting our results.

Tables 3 to 5 presents the main results achieved from the propensity score matching estimation. The outcome from the first stage is, instead, listed in the Appendix (Tables A3.1, A3.2 and A3.3).

In order to account for the heterogeneous composition of the labor force, we define different skill variables and we estimate the impact of our 'treatment', i.e. offshoring, on their variation over time. We first start with the most aggregate indicator, that is the ratio between non-manual and manual workers, the former including high skilled occupations as managers, middle managers and clerks, while the latter comprising low-skilled occupations as operatives (blue-collars).

Both nearest neighbour propensity score with oversampling and with replacement show that the effect of production offshoring on the ATT is always negative but not significantly different from zero. This means that firms choosing to externalize production do not seem to face any particular aggregate skill re-composition dynamics over the sample period.

In order to shed more light on this weak result, we further disaggregate the previous variable in order to analyze the dynamics of each single skill category for the treated and the untreated observations. On this purpose, we identify other four skill variables, whose difference-in-differences constructions are reported in Tab.A.2: managers and middle managers over blue-collars; middle managers over blue-collars; managers and middle managers over clerks and blue-collars; middle-managers over clerks and blue-collars.

Table 3 shows again results for the first two of these new variables. In particular, when looking at the effect of delocalization on **DID_Mng+MMng/Man** we still note a negative but not significant outcome. The outcome changes when we look at the second skill variable, i.e. **DID_MMng/Man**, in which, at the numerator, we identify the probably most skilled component of the workforce. When we allow the propensity score to use the same non-treated observations more than once and we increase the maximal allowed difference in the propensity score of treated and matched untreated, we are able to find a negative and statistically significant result. This means that offshoring firms face a decrease in the employment of skilled personnel, relative to the unskilled.

Very similar results seem to emerge from Table 4, when we simply add clerks at the denominator of both skill ratios. Again, offshoring does not seem to particularly affect the difference over time of (**DID_Mng+MMng/C+Man**), i.e. skilled non-manual over unskilled, both manual and non-manual). A significant and negative effect, even if of small magnitude, emerges when looking at the ratio between (skilled) middle managers and (unskilled) blue collars plus clerks. Manufacturing firms exposed to the offshoring treatment are more likely to suffer a de-skilling re-composition of their workforce over time.

We finally consider the dynamics of each single skill-occupational category. In this case we observe the difference in the relative employment of top managers, middle manages, clerks and blue-collars for the treated and the counterfactuals. In line with previous results, Table 4 and Table 5 show that the most significant effect of production relocation is on middle-managers, with a negative sign.

We can interpret these results in two ways. On the one hand, the results achieved seem to be in line with H1, according to which the defensive nature of the offshoring strategy activates a sort of *substitution effect* that proves to be detrimental for the upskilling dynamics of the workforce. In other words, the fact of de-locating production activities towards cheap-labor countries reduces the overall scale of domestic activity, reducing the demand for managerial, coordination and control skills, thus decreasing the relative number of middle managers for each operative.

On the other hand, we also find a *quantity effect* on the relative employment of skilled personnel. This result can be in line with hypothesis H2 and previous anecdotal evidence, according to which Italian firms delocalizing, for instance, cheap-labor countries face an outflow of managerial skills because of the need to coordinate and manage new, external units of production (Mariotti and Mutinelli, 2005). It is the case of a horizontal replication of domestic activities that, on the one hand, can leave unchanged the domestic skill composition or, on the other hand, can cause the transfer of managerial skill abroad in order to coordinate these new activities under the control of domestic affiliates.

Table 3. The skill composition effects of production offshoring in Italy, 1995-2003

	Outcome Variables								
	DID_NMan/Man			**DID_Mng+MMng/Man**			**DID_MMng/Man**		
Algorithms	**Effect**	**S.E.**	**Number of delocalizing firms off common support**	**Effect**	**S.E.**	**Number of delocalizing firms off common support**	**Effect**	**S.E.**	**Number of delocalizing firms off common support**
NN oversampling									
2	-0.102	0.152	2	-0.018	0.045	2	-0.039	0.024	2
5	0.035	0.108	2	-0.016	0.040	2	-0.024	0.022	2
10	-0.000	0.095	2	-0.011	0.044	2	-0.022	0.025	2
NN with replacement									
cal 0.01	-0.199	0.195	6	-0.024	0.060	6	-0.034	0.028	6
cal 0.02	-0.202	0.195	2	-0.014	0.056	2	-0.047***	0.017	2
cal 0.05	-0.202	0.207	2	-0.014	0.061	2	-0.047**	0.020	2

Table 4. The skill composition effects of production offshoring in Italy, 1995-2003

	Outcome Variables								
	DID_ Mng+MMng/C+Man			**DID_MMng/C+Man**			**Mng/Employment**		
Algorithms	**Effect**	**S.E.**	**Number of delocalizing firms off common support**	**Effect**	**S.E.**	**Number of delocalizing firms off common support**	**Effect**	**S.E.**	**Number of delocalizing firms off common support**
NN oversampling									
2	-0.009	0.039	2	-0.029**	0.014	2	0.018	0.028	2
5	-0.017	0.028	2	-0.025*	0.015	2	0.008	0.018	2
10	-0.008	0.034	2	-0.019	0.019	2	0.011	0.016	2
NN with replacement									
cal 0.01	-0.012	0.056	6	-0.023	0.016	6	0.010	0.026	6
cal 0.02	-0.001	0.050	2	-0.033**	0.016	2	0.028	0.036	2
cal 0.05	-0.001	0.053	2	-0.033***	0.012	2	0.028	0.039	2

Table 5. The skill composition effects of production offshoring in Italy, 1995-2003

	Outcome Variables								
	MMng/E			**Clerks/E**			**Man/E**		
Algorithms	**Effect**	**S.E.**	**Number of delocalizing firms off common support**	**Effect**	**S.E.**	**Number of delocalizing firms off common support**	**Effect**	**S.E.**	**Number of delocalizing firms off common support**
NN oversampling									
2	-0.023**	0.011	2	-0.013	0.045	2	0.030	0.069	2
5	-0.018	0.011	2	-0.001	0.042	2	0.017	0.046	2
10	-0.015*	0.009	2	-0.000	0.038	2	0.012	0.036	2
NN with replacement									
cal 0.01	-0.017	0.011	6	-0.05	0.058	6	0.044	0.076	6
cal 0.02	-0.026**	0.013	2	-0.043	0.058	2	0.046	0.093	2
cal 0.05	-0.026**	0.010	2	-0.043	0.060	2	0.046	0.080	2

5. Concluding remarks

In this work we have assessed the existence of a delocalization effect on the skill composition of the workforce. We tested two hypotheses: first, that production offshoring aimed at labor costs savings generates either a skill-upgrading effect or a skill-downgrading effect; second, that the offshoring of production activities can be a phenomenon of mere replication of domestic activities, thus causing either a skill-biased effect or a general negative effect on the employment of skilled labor. The estimation procedure implemented relies on the so called DID-PSM estimator, that, although grounded on identification assumptions, is not based on a parametric specification and does not rely on optimization restrictions.

The results obtained give the impression that the offshoring strategy of the Italian manufacturing firms does not exert a strong impact on the skill composition of the workforce. The delocalization strategy appears to have an overall neutral effect on domestic occupational categories and on the skill ratios, probably confirming an idea of delocalization as a horizontal replication of domestic activities. Middle-managers appear to be the most affected category by the offshoring decision. Such an evidence may find a twofold explanation. On the one hand, skilled workers can decline more than unskilled workers because of a *substitution* effect that is driven by the seek of economizing on labor costs reducing not only redundant activities, but also reducing the need for intermediate skills such as control, managerial and coordination for which middle-managers are employed for. On the other hand, skilled workers may decline in absolute terms, because of a *quantity* effect that can occur when firms decide to transfer managerial staff in order to coordinate and supervise the activities replicated abroad.

However, due to the limited information available and the small number of firms for the quasi-experiment, the interpretation and validation of these pieces of evidence needs further research.

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Appendix

Table A1-Variable definitions and summary statistics

VARIABLE	DEFINITION	MEAN	STD. DEV.	MIN	MAX
Dependent variable of the first stage probit regression					
d_deloc00	Dummy delocalization	.048	.215	0	1
Control variables					
Lnage	Natural logarithm (2003-year of firm's set-up)	3.402	.572	1.945	7.602
nw	Liguria, Lombardia, Piemonte, Valle d'Aosta	.457	.498	0	1
ne	Emilia-Romagna, Friuli Venezia-Giulia, Trentino Alto-Adige, Veneto	.300	.458	0	1
cen	Abruzzo, Lazio, Marche, Molise, Toscana, Umbria	.160	.367	0	1
south	Basilicata, Calabria, Campania, Puglia, Sardegna, Sicilia	.081	.274	0	1
suppldom	Textiles, footwear, food and beverage, paper and printing, wood	.587	.492	0	1
specsupp	Machinery and equipment, office accounting and computer machinery, medical optical and precision instruments	.412	.492	0	1
lsize	Nat. log average employment size 1998-2000	4.147	1.097	2.335	8.542
breakup9597	=1 if the firm has broken-up at 31.12.1997; =0 otherwise	.015	.122	0	1
breakup9800	=1 if the firm has broken-up at 31.12.2000; =0 otherwise	.039	.194	0	1
group9507	= 1 if the firm belongs to a group at 31.12.1997; =0 otherwise	.227	.419	0	1
group9800	= 1 if the firm belongs to a group at 31.12.2000; =0 otherwise	.257	.437	0	1
Export and FDI					
d_exp97	=1 if the firm has exported in 1995-97; =0 otherwise	1.190	.393	0	1
d_exp00	=1 if the firm has exported in 1998-2000; =0 otherwise	.803	.398	0	1
d_fdi97	=1 if the firm has effected FDIs in R&D in 1995-97; =0 otherwise	.239	.427	0	1
d_fdi00	=1 if the firm has effected FDIs in 1998-2000; =0 otherwise	.018	.133	0	1
Technology					
d_res97	=1 if the firm has invested in R&D in 1995-97; =0 otherwise	1.581	.494	0	1
d_res00	=1 if the firm has invested in R&D in 1998-2000; =0 otherwise	.496	.500	0	1
Unit labor costs					
lcla9597	Nat. log. labor costs per employee 1995-97	3.453	.620	1.873	5.617
lcla9800	Nat. log. labor costs per employee 1998-2000	3.297	.259	2.256	4.230

Productivity					
lfatta9597	Nat. log. sales per employee 1995-97	5.245	.760	3.536	7.395
lfatta9800	Nat. log sales per employee 1998-2000	3.444	.386	2.753	4.774
Capital intensity					
litna9597	Nat. log. net capital assets per employee 1995-97	3.411	1.009	-.366	5.826
litna9800	Nat. log. net capital assets per employee 1998-2000	3.315	.875	-.274	5.443
Asset specificity and uncertainty					
llev	Debt/Asset ratio 1998-2000	-.493	.307	-2.082	-.025
un9800	Variance of the annual percentage rate of variation in total sales, 1998-2000	.044	.282	0	5.038
lev_unc9800	Asset Specificity * Volume Uncertainty	.018	.047	0	.341
Profitability					
roi9800	Returns on investments 1998-2000	.067	.056	-.119	.372

Table A2. Outcome variables*

Outcome variables construction	
DIDNonManuals/Manuals (**DID_NMan/Man**)	[(NonManuals/Manuals)$_{03}$-(NonManuals/Manuals)$_{00}$]-[(NonManuals/Manuals)$_{98}$-(NonManuals/Manuals)$_{95}$]
DIDManagers+MidMans/Manuals (**DID_Mng+MMng/Man**)	[(Managers+MidMans/Manual)$_{03}$-(Managers+MidMans/ Manuals) $_{00}$] – [(Managers+MidMans/Manuals)$_{98}$ - (Managers+MidMans/Manuals)$_{95}$]
DIDMidMans/Manuals (**DID_MMng/Man**)	[(MidMans/Manuals)$_{03}$-(MidMans/Manuals)$_{00}$]-[(MidMans/Manuals)$_{98}$-(MidMans/Manuals)$_{95}$]
DIDManagers+MidMans/Clerks+Manuasl (**DID_ Mng+MMng/C+Man**)	[(Managers+MidMans/ Clerks+Manuals)$_{03}$-(Managers+MidMans/ Clerks+Manuals) $_{00}$] - [(Managers+MidMans/ Clerks+Manuals)$_{98}$ - (Managers+MidMans/ Clerks+Manuals)$_{95}$]
DIDMidMans/Clerks+Manuasl (**DID_MMng/C+Man**)	[(MidMans/Clerks+Manuals)$_{03}$-(MidMans/Clerks+Manuals)$_{00}$]- [(MidMans/Clerks+Manuals)$_{98}$-(MidMans/Clerks+Manuals)$_{95}$]
DIDManagers/TotalEmployees (**DID_ Men/E**)	[(Managers/TotalEmployees)$_{03}$-(Managers/TotalEmployees) $_{00}$] - [(Managers/TotalEmployees)$_{98}$ - (Managers/TotalEmployees)$_{95}$]
DIDMidMans/TotalEmployees (**DID_ MMng/E**)	[(MidMans/TotalEmployees)$_{03}$-(MidMans/TotalEmployees) $_{00}$] -[(MidMans/TotalEmployees)$_{98}$ - (MidMans/TotalEmployees)$_{95}$]
DIDClerks/TotalEmployees (**DID_ C/E**)	[(Clerks/TotalEmployees)$_{03}$- (Clerks/TotalEmployees) $_{00}$] - [(Clerks/TotalEmployees)$_{98}$-(Clerks/TotalEmployees)$_{95}$]
DIDManuals/TotalEmployees	[(Manuals/TotalEmployees)$_{03}$- (Manuals/TotalEmployees) $_{00}$] -

(**DID_ Man/E**)	[(Manuals/TotalEmployees)$_{98}$-(Manuals/TotalEmployees)$_{95}$]

* Note: DID is the acronym Difference-In-Differences

Table A3.1. First-stage probit regression

Dependent variable: **d_deloc00**	**Coef.**	**S.E.**	**z**
lnage	0.665**	0.287	2.32
nw	-0.864	0.649	-1.33
ne	-0.083	0.596	-0.14
cen	-0.298	0.687	-0.43
lsize	0.098	0.190	0.52
specsupp	0.716*	0.379	1.89
group00	0.882*	0.473	1.86
breakup00	-0.554	0.758	-0.73
d_res00	-0.675*	0.391	-1.72
d_fdi00	2.044***	0.767	2.66
group9597	-0.519	0.522	-0.99
d_res9597	-0.304	0.331	-0.92
d_fdi9597ue	-0.384	0.407	-0.94
litna9800	0.235	0.293	0.8
roi9800	-1.991	3.330	-0.6
lnfatta~9800	2.159***	0.818	2.64
lcla9800	-2.425**	0.993	-2.44
litna9597	-0.428	0.337	-1.27
roi9597	0.003	0.004	0.88
lfatta9597	-1.711**	0.821	-2.08
lcla9597	2.166**	0.859	2.52
constant	-5.018*	2.607	-1.92
Log likelihood		-46.022	
Number of obs		321	
LR chi2(21)		35.11	
Prob > chi2		0.027	

Table A3.2. Description of the propensity score in the common support region

	Percentiles	**Smallest**		
1%	0.032	0.031		
5%	0.032	0.032		
10%	0.035	0.032	Obs	120
25%	0.047	0.032	Sum of Wgt.	120
50%	0.072		Mean	0.121
		Largest	Std. Dev.	0.125
75%	0.126	0.444		
90%	0.252	0.537	Variance	0.015
95%	0.404	0.631	Skewness	2.675
99%	0.631	0.781	Kurtosis	11.407

Table A3.3. Inferior bound, number of treated and number of controls in each block

Inferior	**dummy**	**offshoring**	
of block		1998-2000	
of pscore	0	1	**total**
0.0319967	91	9	100
0.2	9	4	13
0.4	4	1	5
0.6	0	2	2
Total	104	16	120
The final number of blocks is 4:			
this number of blocks ensures that the mean propensity score is not different for treated and controls in each blocks			

Notes: the output here reported is that one of the STATA module developed by Ichino and Becker (2002).

Figure A1 – Skill ratios trends in delocalizing and non-delocalizing firms on common support

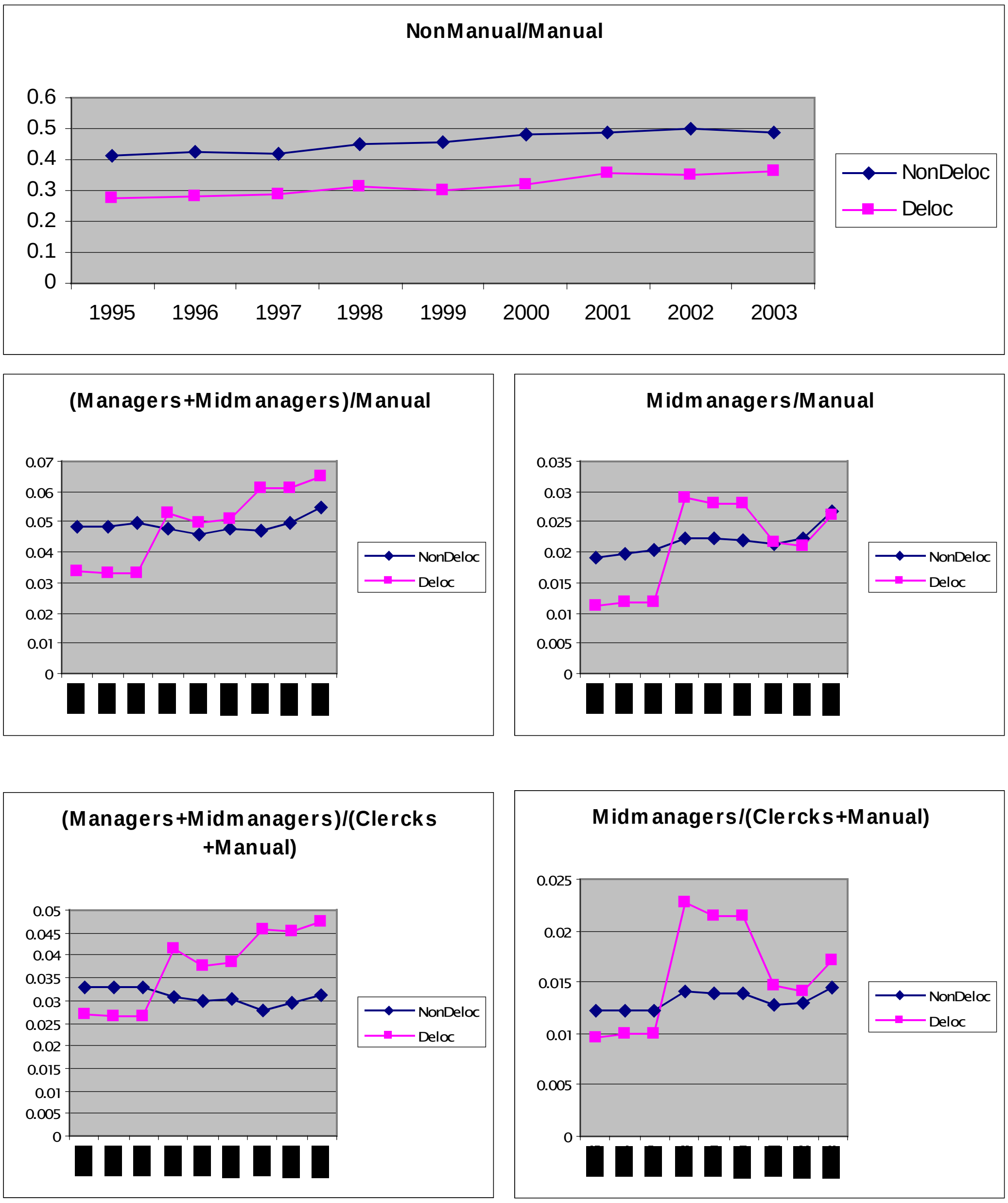


Figure A2 – Occupational categories trends in delocalizing and non-delocalizing firms common support

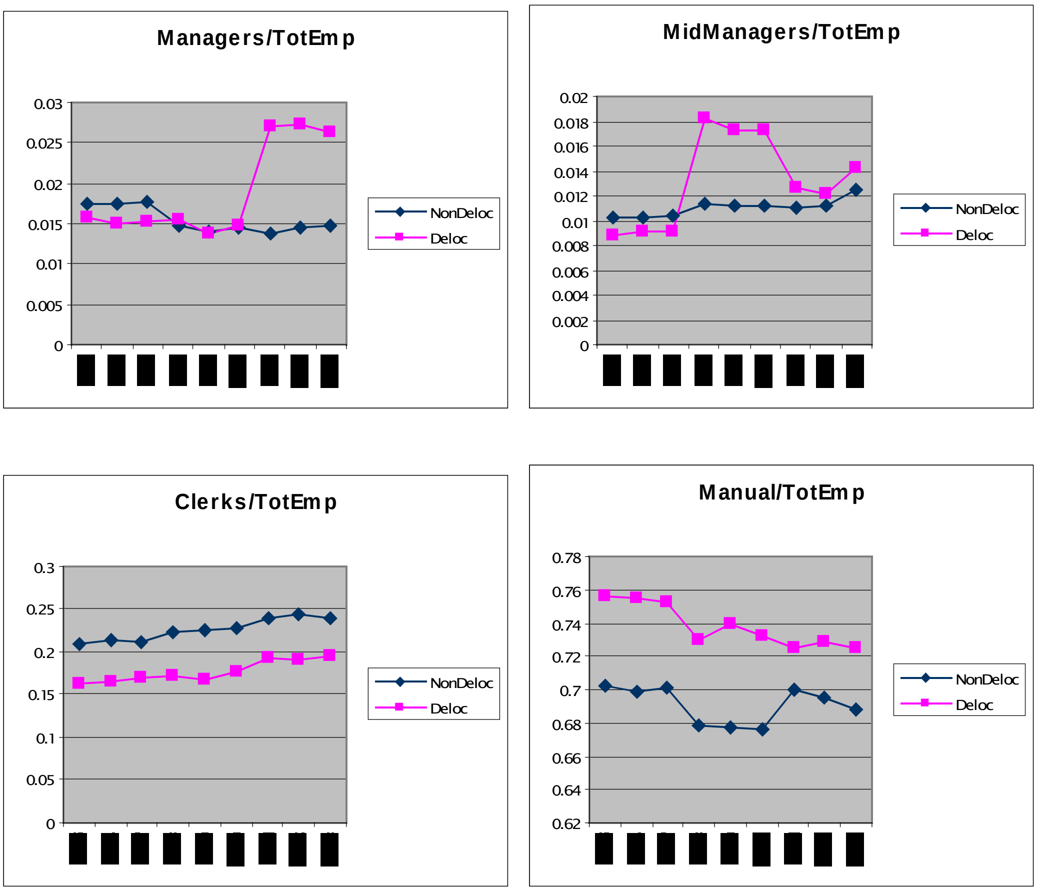
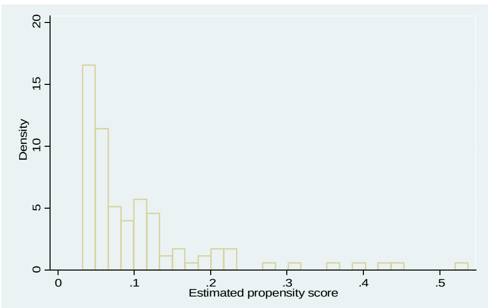


Figure A.3 Common support for all firms

D=0



D=1