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Production offshoring and the skill composition of Italian manufacturing firms: a counterfactual analysis

Roberto Antonietti[1] and Davide Antonioli[2]

Abstract

In this work we explore how the international outsourcing of production (offshoring) impacts the skill composition of Italian manufacturing firms. In particular, our aim is to assess if the choice to offshore production activities to cheap-labour countries implies a bias in the employment of skilled workers relative to unskilled workers.

Using a balanced panel of firms across the period 1995-2003, we set up a counterfactual analysis in which, by using a difference-in-differences propensity score matching estimator, we compare the dynamics of skill demand for treated and control firms while addressing the possible problem of selection bias.

Our results point to identify a "potential" skill bias effect of production offshoring. In particular, we find that treated firms tend to show an upward shift in the skill ratio with respect to the counterfactual sample, but coefficients are not significantly different from zero. When we look at the elements of the skill ratio separately, we find that the skill bias is significantly driven by a fall in the employment of production workers (blue collars), rather than by the increase in the employment of nonproduction workers (white collars), thus providing further evidence on the unskilled labour-saving nature of international outsourcing.

Keywords: production offshoring, skill-bias, difference-in-differences, propensity score matching

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1. Introduction

During the last three decades the way goods are manufactured has dramatically changed. A new international division of labour has emerged that is characterised by firms fragmenting the entire value chain – from product design to assembling and distribution - into modules that are moved to different locations on a global scale in order to exploit localization advantages and factor costs differentials.

The fall in trade barriers and transportation costs, the rapid diffusion of information and communication technologies and the recent economic transformations occurred in Eastern Europe, together with the emergence of countries like Brazil, China, India and Russia, have been responsible of the recent increase in the international fragmentation of production in Western economies. Concerning this, trade statistics show a steady increase of intra-industry trade flows (in the form of outward processing trade) between European Union and the rest of the world in a relatively short period of time (Mariotti and Mutinelli 2005; UNCTAD 2006; Baldone, Sdogati and Tajoli 2007).

In this framework, Italy can be considered as a late comer with respect to the other European partners: the characteristics of its industrial composition, primarily made by small and medium firms, have typically represented a barrier to the development of activities on an international scale (Onida 2004; Federico 2006). The current volume of foreign direct investments (FDI) on GDP, for instance, is still scarce if referred to the amount of FDI flowing out from other comparable industrialised economies (UNCTAD 2006). Nevertheless, the overseas delocalization of production and service activities has rapidly increased also in Italy, particularly involving those sectors (the so called *Made in Italy*: food, textile and clothing, industrial machinery, furniture) in which firms show a high level of specialization (Centro Studi Capitalia 2001, 2004; Helg and Tajoli 2005; Falzoni and Tajoli 2008)[3].

[3] According to Centro Studi Capitalia (2001, 2004), the share of firms offshoring production raised from 2% to 5% between 1998 and 2003. Falzoni and Tajoli (2008), relying on input-output data provided by the National Statistical

One of the main consequences of this phenomenon is that, next to an extensive use of IT capital, imported materials and intermediate services, an increasing replacement of low-skill employment is occurring due to the fact that firms are sub-contracting the less knowledge-intensive activities. Trade flows, import competition and FDI, thus, can result in a reorganization of production through which home firms can specialize on the high-value-added phases of the value chain while economizing on production costs.

The increasing fear of job losses, particularly referred to low-skill intensive tasks and occupations, is making international fragmentation of production a 'hot topic' both for medias and for academic research. 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 non-neutral 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 labour markets (like in the US and UK) or to increase the relative unemployment of less qualified workers in relatively more rigid ones (as in Germany, France, Denmark and Italy).

The second claims for increased international trade and globalization of production, according to which labour is relocated in a way that determines a shift of redundant and routinized activities toward less-developed countries, while keeping non-routinized, high skill-intensive activities at home, thus increasing the domestic firms' comparative advantage in the production of high-value added goods.

Recent international evidence (Brainard and Litan 2004; Amiti and Wei 2005), however, shows also that the increasing digitization of production enables firms not only to offshore pure manufacturing processes, but also service activities like software programming, medical diagnosis, lab research, product development and analytical activities, hence creating the conditions for the transfer of knowledge-intensive jobs.

Office (ISTAT), find that, while service offshoring increased from a 0.52% in 1992 to 2.06% in 2003, the offshoring of materials and goods raised in the same period from 18.34% to 26.42%.

With this piece of work we aim at assessing if, and to what extent, the firm's decision to offshore production to low-wage countries alters the skill intensity of domestic employment. On this purpose, we conduct our empirical exercise in a framework closed to a laboratory experiment, in which we employ a semi-parametric difference-in-differences propensity score matching estimator in order to control for sample selection and unobserved heterogeneity among observations and across the years.

Our counterfactual analysis is developed on a sample of Italian manufacturing firms that have been active from 1995 to 2003. The estimation results seem to support the possible existence of a skill-bias effect of production offshoring, but only driven by a fall in the demand for unskilled workers.

The article is structured as follows. Section 2 briefly reviews the empirical literature focused on the skill-bias effects of offshoring. Section 3 describes data and the empirical methodology adopted. Section 4 presents and discusses the estimation results and section 5 concludes.

2. Background literature

Even if it is considered a 'hot topic' for economists, the impact of globalization on the international division of labour and the employment dynamics of workers is still ambiguous.

After trade and technological change, international fragmentation, international outsourcing and offshoring have been considered as potential explanations for the rising income and employment differentials between skilled and unskilled workers (Feenstra and Hanson 1996; Egger and Falkinger 2003; Chusseau, Dumont and Hellier 2008). However, the question if the international relocation of production determines a change in the skill intensity of jobs is still unanswered, both in theory and in the evidence. While traditional trade models based on the Hecksher-Olin-Samuelson framework argue that the move of low-skill intensive stages of production abroad decreases the demand for the relatively less abundant factor at home, other studies predict a more ambiguous impact of international outsourcing on low-skilled workers in the source country (Arndt 1997; Glass and Saggi 2001; Jones and Kierzkowski 2001).

What seems to emerge from the theoretical literature is that such effect depends on which type of production or service is offshored, on the factor intensity of both the processes that remain in the home country and the ones that are relocated internationally (Kohler 2003; Egger and Falkinger 2003; Egger and Egger 2003), and, finally, on the sector in which offshoring occurs (Arndt 1997).

The empirical literature on the skill bias effects of international outsourcing can be divided in two main lines of research. A first set of studies looks at offshoring in terms of FDI and distinguishes between vertical and horizontal FDI (Markusen et al. 1996; Lipsey 2002). While the former is mainly driven by the will of exploiting the differences in factors endowments and prices, and leads to a net decrease in domestic employment (Agarwal 1997; Braconier and Ekholm 2000; Mariotti, Mutinelli and Piscitello 2003), the latter is primarily driven by the will to replicate abroad the whole production process of the home country, with the aim of finding new markets and global opportunities and with the effect of increasing both the employment and the skill intensity of domestic jobs (Markusen et al. 1996; Blömstrom, Fors and Lipsey 1997; Mariotti, Mutinelli and Piscitello 2003).

A particular, and still less explored, issue concerns the effect of FDI and offshoring on the quality of labour, i.e. on the skill composition of employment. The question becomes: does investing in cheap-labour countries lead to a skill upgrading at home?

Head and Ries (2002) try to answer this question by looking at Japanese multinationals in the period 1965-1990: their results point to a positive relationship between offshoring and the demand for skilled labour only if production re-location is directed to developing countries and only when the unit of analysis is the firm instead of the industry. Similarly, Hansson (2004) finds that production delocalization toward less developed countries contributes to the general increase in the average level of qualification within Swedish multinationals. In contrast with these results, Slaughter (2000), looking at 32 US manufacturing industries in the 1980s, does not show clear results in favour of the positive relationship between FDI and the employment of skilled workers at home.

For Italy, Castellani, Mariotti and Piscitello (2008), merging the Reprint dataset provided by the national Institute for Foreign Trade (ICE) with the Outlook on Balance Sheets of Italian incorporated companies and the Excelsior database on Italian employment provided by the national Chambers of Commerce (Unioncamere) for the period 1998-2004, find a skill upgrading effect only for firms investing in Central and Eastern Europe with respect to firms that remained domestic. Relying on the Capitalia dataset and working on a sample of about 500 manufacturing firms over the 1980s and over the 1990s respectively, Piva and Vivarelli (2002, 2004) also do not find any significant effect of FDI on the skill composition of Italian employment, even if the nature of the data and of results do not exclude *a priori* any possible influence[4].

A second group of studies, primarily based on the "new international trade theory", focuses instead on the increasing fragmentation of production and looks at international outsourcing as a relatively new form of trade involving intermediate goods and processes. 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, "outsourcing" refers to the relocation of jobs and processes to external providers regardless of their location, while "offshoring" refers to the relocation of jobs and processes to any foreign country, without distinguishing whether the provider is external or affiliated with the firm[5]. The term "offshoring outsourcing", instead, strictly covers the relocation of jobs and activities to an external and internationally located provider (Olsen 2006)[6].

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[4] Similar results also emerge when looking at international joint ventures (JVs) of Italian firms. In this respect, Barba Navaretti, Santarelli and Vivarelli (2002), for instance, relying on a cross-sectional dataset of 172 JVs interviewed in 1998, find that only JVs motivated by the search for lower labour costs, as well as those established with East European firms, are associated with a higher employment performance with respect to the average.

[5] Alternatively, the Oxford English Dictionary defines offshoring as the action or practice of moving or basing a business operation abroad, usually to take advantage of lower costs (http://dictionary.oed.com/).

[6] The partial or total transfer of the production of goods or services abroad to non-affiliated enterprises, through subcontracting abroad, is defined by OECD (2007) as offshoring in the broad sense.

The evidence available from the international trade literature provides general support for the skill-biased nature of production relocation[7]. Wood (1994), for instance, calculates that import competition determines a reduction in the demand for unskilled labour by 30% in 1990. On the same line, Sachs and Shatz (1994) conclude that production internationalization exerts a double effect on overall labour 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) provide 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 supported by Hijzen, Görg and Hine (2004), who show that, between 1982 and 1996, international outsourcing has a strong negative impact on the demand for semi-skilled and unskilled labour.

For France, Strauss-Khan (2003) 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.

For Austria, instead, a positive and significant effect on skilled labour comes out only when using proxies of international trade like export openness and outsourcing, while a negative effect arises when considering import penetration (Dell'mour et al. 2000).

For the Italian case, finally, the scanty evidence seems to support the positive relationship between offshoring and the relative demand for skilled labour. Helg and Tajoli (2005), for instance, compare the effect of international fragmentation of production (computed from input-output data on

[7] For a comprehensive survey on North-South trade models explaining the widening wage inequality between skilled and unskilled workers see Chusseau, Dumont and Hellier (2008).

outward processing trade) on the skill ratio on 20 manufacturing sectors in Italy and in Germany during the 1990s and show that a positive and significant impact emerges only for the former, while for the latter the effect seems to be not significant[8].

Summing up, the most recent literature on skill-bias international fragmentation seems to 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, together with different measurement and econometric techniques, matter in explaining these effects.

3. Methodology and data

3.1. Data

The dataset consists in a sample of Italian manufacturing firms drawn from the VII, VIII and IX waves of the Survey on Manufacturing Firms (*Indagine sulle Imprese Manifatturiere*) provided by Capitalia (formerly *Mediocredito Centrale*) and covering the period 1995-2003. Interviews were conducted respectively in 1998, 2001 and 2004. For each survey all the firms with more than 500 employees were interviewed, while for those firms having more than 11 employees and less than 500 the Survey identifies a representative sample stratified by geographical area, industry and employment size. The three waves, 1995-1997, 1998-2000 and 2001-2003 gather information on 4.497, 4.680 and 4.289 firms respectively.

In order to work on a balanced panel, we first merge the three surveys and we identify a sample of 414 firms always present across nine years. Firms offshoring production in 1998-2000 are 16 (3.8%) out of 414, which are a slightly overrepresented sample with respect to the percentage (1.9%) that emerges when we look only at the full 1998-2000 wave (Centro Studi Capitalia 2001).

[8] Similar results for the German case emerge also in Fitzenberger (1999) and Falk and Koebel (2000), who find no evidence that international outsourcing of production and services positively affect the skill composition of manufacturing workforce. Rather, Fitzenberger leaves technology the dominant role in shifting away the employment of unskilled workers.

In order to avoid bad matches in the construction of the counterfactual, we further dropped observations belonging to industries (classified by ATECO 1991 standard, in line with ISIC Rev. 3.1 and NACE Rev. 1.1) in which no firm has moved production abroad. For the same reason, we also excluded other groups of firms potentially conducive to misleading results. Specifically, we first dropped firms with missing values in balance sheets data; then we dropped firms having undergone takeovers or break-ups and, finally, firms which delocalized production before and after the treatment period 1998-2000[9]. This passage is particularly important for the correct specification of the treatment variable. In our case, we select only those firms that offshored production in 1998-2000, so that we avoid any possible spurious effect on the outcome coming from previous or subsequent offshoring activities. At the end of this procedure we obtain a panel of 184 firms suitable for the analysis.

The structure of the sample is reported below. Table 1a shows the distribution of firms by industry and employment classes. As expected, the major part of the firms in our final sample is of small and medium size, and this holds for each industry coded by 2-digit ATECO 1991 standard (textile and clothing, leather and footwear, chemicals, rubber and plastics, metal products, industrial machinery).

TABLE 1a AROUND HERE

Table 1b, instead, shows the structure of the sample by employment classes and geographical area and compares the merged sample (1995-2003) before and after data cleaning with the two original

[9] It must be stressed that, in the period under examination, offshoring is still a limited phenomenon in Italy. In particular, according to Centro Studi Capitalia (2001, 2004), it involves about 2% of firms in 1998-2000 and about 5% of firms in 2001-2003. In each Survey, the question used to identify offshoring firms is the following: "Did the firm delocalize its own production activities in Central-Eastern European Countries (Poland, Czech Republic, Slovakia, Hungary, Romania, Bulgaria) and ex-Yugoslavia during the triennium 1998-2000?"

surveys (1995-1997 and 1998-2000) and with 2001 Census data as given by National Statistical Office (ISTAT 2001).

TABLE 1b AROUND HERE

If we look at the last two columns of Table 1b, it is easy to note that the cleaning process has led to a re-alignment of the sample to the original structure of the data. However, although in line with the first survey (1995-1997), if compared with Census data, the final (after cleaning) sample slightly over-represents middle and large firms, and firms located in the North of Italy. This bias basically arises for two reasons. First, the Capitalia samples are stratified such that larger firms are much more likely to be included, and this occurs because firms with more than 500 employees are totally included (by Census) while firms with less than 500 employees are sampled on the base of their geographical location, sector of economic activity and size. Second, small firms generally show both a higher propensity to exit the market and a higher propensity to be merged with other firms, so that, in a panel structure, they are much more likely to be excluded than larger firms.

Table 2 instead shows the distribution of treated and untreated units by industry, employment size and geographical area.

TABLE 2 AROUND HERE

From a strict econometric point of view, the limited number of treated units does not represent a crucial issue for the application of the empirical analysis. What is important is the relative dimension of the untreated sample, which needs to be large enough in order to draw an appropriate counterfactual set. The basic idea of matching estimations is to find in a large group of non-participants in the treatment the firms which are similar to the participants in all relevant pre-treatment characteristics. In our case, the ratio between treated and untreated units is 1 to 25, so that the pool of possible control units is relatively large and the counterfactual analysis reliable. Table 3 shows some summary statistics for offshoring and non offshoring firms[10].

TABLE 3 AROUND HERE

The Table summarizes the variables that are supposed to be relevant in the following empirical analysis, as they can potentially affect both the propensity to move production abroad (see section 3.3) and the demand for skills. In particular, we focus on investments in technology (i.e. ICT equipment), the export activity, the composition of the workforce by occupation, the capital intensity, the average productivity and the labour cost per employee[11].

As we can see, the average size of treated units is higher than the average size of untreated; in addition, the treated sample is characterized by a slightly lower share of skilled workers (0.357) than the untreated sample (0.479) and a higher share of unskilled workers (0.767). If the offshoring of low-skill intensive activities to cheap-labour countries is responsible for such a picture is the object of the following empirical exercise.

Notwithstanding these differences, simple t-tests did not reject the hypothesis of the equality of means between treated and control units[12].

However, the limited number of treated firms leads us to consider our empirical exercise more like an explorative experiment rather than a representative analysis of the Italian manufacturing industry.

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[10] Summary statistics for the merged sample are reported in Table A2 in the Appendix.

[11] See the Appendix for a more detailed description of the variables.

[12] The results of the t-test are not reported here, but are available on request. The balancing property test described in Section 3.4 also confirms that our treated observations are not different than counterfactuals.

3.2. Empirical methodology

Empirical studies testing the skill-biased international trade hypothesis are generally based on the estimation of short-run cost functions, reflecting the cost-minimizing behaviour of firms. The most utilised flexible cost function is generally the dual of the transcendental logarithmic production function, as proposed by Christensen, Jorgenson and Lau (1973).

However useful, this approach suffers from two major limitations: on the one hand, it relies on a "simple" cost function framework, which is subject to a set of *ad hoc* regularity conditions – i.e. symmetry and homogeneity of parameters and constant returns to scale - that are necessary for its analytical tractability; on the other, it is linked to a specific functional form that constraints the parameters to assume specific values[13]. Furthermore, if only limited information is available on the employment composition and on firms' characteristics, a possible problem of sample selection may arise, according to which the set of firms which decide to transfer production abroad cannot be thought as randomly drawn from the whole population.

In the following analysis, instead, we employ a treatment effect estimation based on matching a certain set of offshoring firms (treated group) with a counterfactual set of firms that are supposed to be similar on the base of a certain vector of relevant characteristics X. Since conditioning on all relevant covariates is a "data hungry" process in case of a high dimensional vector X[14], Rosenbaum and Rubin (1983) suggest to use the so called balancing score $b(X)$, i.e. a function of the relevant observed covariates X such that the conditional distribution of X given $b(X)$ is independent of assignment into treatment.

In this paper we employ a semi-parametric approach based on propensity score, i.e. the probability to be assigned into a treatment conditional on observed characteristics, developed within the

[13] See Barnett, Lee and Wolfe (1985) and Dumont (2005) for a treatment of the drawbacks linked to the use of a translog cost function. In particular, Barnett (1985) shows how the translog function tends to violate regularity conditions within the data region.

[14] This problem is defined as 'curse of dimensionality'.

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).

Propensity score matching (PSM) has become a popular approach for estimating causal treatment effects and it is a more flexible technique with respect to standard labour demand estimation: first, it does not force the imposition of a parametric specification of the relations of interest; second, it allows to handle the selection bias that can occur when dealing with potentially endogenous variables; third, when applied to longitudinal data, it allows to tackle the issue of unobserved heterogeneity among observation. In particular, the difference-in-differences (DID) matching estimator (Heckman, Ichimura and Todd 1997) helps to remove temporally invariant differences in outcomes between treated and untreated units that can persist even once conditioning on observables.

The DID-PSM consists of a two-stage model of estimation. In the first stage, one should estimate the probability to be assigned into treatment given a certain set of observables, which are supposed either to be fixed over time or to be measured before the assignment into the treatment.

In the second stage, one should use the propensity score in order to estimate the average treatment effect on the treated (ATT). In our case the outcome variables are the difference-in-differences of the skill ratio of the workforce and the difference-in-differences of the employment share by occupational category.

When choosing the matching algorithm, the high number of potential controls for each treated unit makes appropriate and feasible the use of the nearest neighbour (NN) method, which allows to match one treated unit with one counterfactual, thus minimizing the bias in the estimation (Caliendo, Hujer and Thomsen 2005; Smith and Todd 2005; Caliendo and Kopeinig 2008).

The ATT is then computed in the following way:

$$A\hat{T}T = \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\Delta Y_i^t - \sum_{j=1}^{N_t} W(i,j)\Delta Y_j^c\right)$$

where N_t is the number of offshoring firms, ΔY is the difference between the outcome variables (i.e. the skill ratios) before and after the participation into the treatment, and W is the weight assigned to each comparison unit in the construction of the counterfactual outcome. Both treated and untreated units are intended to be on the common support[15].

The main aim of the DID-PSM method is to generate a set of non-offshoring (not treated) firms as much similar as possible to the offshoring (treated) ones in order to get a proxy of what would have happened to domestic skill composition within offshoring firms if they had not chosen to relocate activities abroad and then testing whether the outcome of the offshoring firms significantly differ from that of the counterfactual (non offshoring) group[16].

3.3. Propensity score estimation

A crucial hypothesis that needs to be satisfied in order to correctly implementing the PSM can be expressed as follows:

$$D \perp X \mid P(X)$$

where $P(X)$ is the propensity score, D the treatment variable and X the observable variables. The condition means that the balancing of the pre-treatment variables is satisfied given the propensity score. Put it another way, the balancing property is satisfied "when observations with the same propensity score […] have the same distribution of observable (and unobservable) characteristics independently of treatment status" (Becker and Ichino 2002, p. 2).

[15] Due to the small dimension of our sample, we adopt a NN DID-PSM estimator with replacement.

[16] The works of Caliendo and Kopeinig (2008) and Smith and Todd (2005) provide a useful guidance for the practical implementation of the matching procedure.

For the empirical implementation of PSM we first estimate the probability of being an offshoring firm (the propensity score), conditional on a set of observable characteristics[17]. Since our treatment is a binary variable, we choose a probit specification. Furthermore, since the matching strategy relies on the conditional independence assumption (CIA) requiring that the outcome variables must be independent of treatment conditional on the propensity score[18], we select variables *X* that credibly satisfy this condition. The *X*s 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 labour force. Following the theoretical and empirical literature on the determinants of international outsourcing, after controlling for firms' geographical location and year dummies, we consider unit labour cost (Abraham and Taylor 1996), export propensity (Görg and Hanley 2004), the adoption of ICT and network technology (Tomiura 2004; Bartel, Lach and Sicherman 2005), as well as other structural variables like capital intensity (net capital stock over net sales) and average productivity (net sales per employee), and the lagged dependent variable, i.e. the pre-treatment skill ratio.

In order to avoid problems of over-parameterization (Bryson, Dorsett and Purdon 2002), we choose a quite parsimonious set of variables for the first-stage specification of the model. Although it leaves the estimates unbiased, including too many variables in our model can increase their variance and can easily lead to the absence of a common support for treated and control units. Moreover, the

[17] The propensity score is estimated on the basis of all the longitudinal information available (552 observations), in order exploit as much information as possible.

[18] The identification assumption may be expressed as:

$$E[Y^0(t=1)-Y^0(t=0)\mid X, D=1] = E[Y^0(t=1)-Y^0(t=0)\mid X, D=0]$$

where Y^0 is the outcome of the untreated units, *D* is the binary variable that indicates the treatment, *t* represents the time ($t=0$ before the treatment and $t=1$ after the treatment), *X* is a vector of conditioning variables. If this assumption holds, it means that the average outcome for treated and untreated would have followed the same path in the absence of treatment conditional on the vector of observable characteristics *X*.

set of relevant variables have been chosen on the base of our knowledge of the related literature and on their statistical significance, as suggested by Caliendo and Kopeining (2008).

The probit estimates show expected results[19]. Given the estimated coefficients of unit labour costs, as well as the ones of technology and export, are significant and positive it can be inferred that the main driving forces behind production offshoring are the will to save on wage and labour costs on the one side, and the previous adoption of ICT and the propensity to explore new markets through export on the other.

3.4. Assessing PSM quality: the balancing property

The next step in our analysis is to assess the quality of the matching. Since we determine the common support by conditioning on the propensity score, we have to check if the matching procedure can balance the distribution of the relevant variables in both the treatment and control group.

Different methodologies can be employed for testing the balancing property: the basic idea of these approaches is to compare the situation before and after matching and check if there remain any differences after conditioning on the propensity score. If this is the case, and if there is still dependence on X, it means that the model could be not properly specified or the CIA could not hold (Smith and Todd 2005; Caliendo and Kopeinig 2008).

For our purpose, we adopt the stratification test developed by Deheja and Wahba (1999, 2002), and further implemented by Becker and Ichino (2002), according to which observations are divided into blocks based on the estimated propensity score, such that no statistically significant difference between the mean of the estimated propensity score in both the treatment and control group remains. Standard *t*-tests are then performed within each block in order to check if the distribution

[19] The probit results and for the figure of propensity score distribution between treated and untreated are not reported here, but are available on request. Here we simply stress that the propensity score distribution is similar for both treated and untreated, being skewed to the left for both the groups.

of the *X* variables is the same between both groups; if any difference still remains, then blocks are further divided and the test repeated until the mean propensity score is the same between treated and counterfactual units.

As can be seen from Table 4, the algorithm identifies two blocks within which the balancing property is satisfied. This means that, in each block, the mean propensity score for treated firms is not different from the one of the counterfactuals.

TABLE 4 AROUND HERE

4. Empirical evidence

4.1. Preliminary analysis

A preliminary step in our counterfactual exercise consists in comparing the dynamics of the dependent variables in our treated and untreated samples as reported in Figure 1. If we look at total employment over time, we see that, although starting from a higher average level, treated units face a sharper decline in occupation than control units after the treatment.

When focusing in detail on the dynamics of the non-production workers (proxied by white collars and including managers and officials, middle managers and executives, clerical staff) and production workers (proxied by blue collars and mainly including plant operators) employment shares the first difference to be noted concerns the relative position of white collars (WC) and blue collars (BC) shares in treated and untreated samples. Untreated units have in both periods higher shares of WC than treated once, while the opposite holds when we consider BC. In addition, after the offshoring period the trend of WC share seems to diverge for the two groups of firms, growing for untreated and decreasing for treated. As far as BC share is concerned we note a sharp decline in its value after the treatment for the firms, while for untreated the value of the BC share remains stable.

The last box in Figure 1 graphically summarizes the behaviour of the skill ratio over time, i.e. the share of non-production workers over production workers. As it can be easily seen, the initial gap in favour of non offshoring firms tends to decrease after the treatment: in front of a relatively stable trend of the skill ratio for the untreated units, the skill ratio of the treated sample seems to raise from an average of 0.3 in 1995-97 to an average of 0.4 in 2001-03[20].

Generally speaking, the similar dynamics of each variable in the pre-treatment period between treated and untreated observations seems to support the validity of the identification assumption at the basis of the DID-PSM estimation: in the absence of the treatment, the outcome of the treated and of the untreated units would have followed equally distanced and stable paths over time.

In the following empirical analysis we investigate if, and to what extent, the treatment we consider (the fact of moving production abroad to cheap labour countries) may have played a role in modelling the skill employment dynamics illustrated in Figure 1. More in detail, we estimate if firms that moved production abroad in 1998-2000 employ, in average, a higher/lower share of skilled labour with respect to firms that, although could have been potentially moved production abroad, did not do that.

FIGURE 1 AROUND HERE

4.2. Estimation results

We now turn the attention to the estimation results. Our analysis consists in the estimation of a two stage selection model, in which we first estimate the probability of a firm to be selected for the treatment (i.e. the decision to relocate production to cheap-labour countries), given a certain set of characteristics, and we secondly estimate the ATT on the base of the propensity score determined in

[20] This also suggests the potential absence of any major unobserved shock that can have affected the workforce skill composition starting from the period 1998-2000.

the first stage.

The dependent variable, i.e. the skill ratio, is calculated, in line with recent literature (Berman, Bound and Griliches 1994; Piva and Vivarelli 2004; Helg and Tajoli 2005), as the ratio between non-production workers and production workers. In addition, we repeat the analysis for the relative employment share of white collars (i.e. the numerator) and the relative employment share of blue collars (i.e. the denominator) separately, so to analyse the effect of offshoring on each element of the skill ratio. Finally, we construct an alternative indicator for unskilled employment by summing up the relative share of blue collars and the relative share of clerical workers. In this way, we build an alternative indicator which includes the semi-skilled and the unskilled components of the labour force (see Hijzen, Görg and Hine 2004)[21].

Tables 5 to 8 show the outcome of the estimations. In Table 5, we estimate the effect of offshoring production on four specifications of the skill ratio (*WC/BC*): the first row is the difference between the average skill ratio in 2001-03 (post-treatment period) and the average skill ratio in 1995-97 (pre-treatment period); the second, third, and fourth rows concern the difference between the skill ratio in each year after the treatment respectively (2001, 2002, and 2003) and the average skill ratio in the period before offshoring occurred (i.e. 1995-97).

In order to control for different specifications of the DID-PS, we estimate two types of ATT: the first (ATT-1) is based on a first-stage DID-PS where we applied a logarithmic transformation to each continuous variable defining the characteristics of the firm (*ULC*, *K/Y*, *Y/L*, *WC/BC*), so that each coefficient of the estimation can be though in terms of elasticity. The second (ATT-2), instead,

[21] In alternative, following the OECD (1998) classification, with this indicator we represent high-skilled and low-skilled blue-collars. We also build an indicator for high-skilled and low-skilled white collars, summing up separately the relative shares of managers and executives. However, due to the high number of firms with zero managers and zero executives, and operating a logarithmic transformation of their ratio, we miss too many information, so that our estimates, although significant, are not totally reliable and comparable with the ones of blue-collars. Tables and outputs on white collars estimations are not reported here, but are available on request

is based on a DID-PS calculated by holding each continuous variable in levels, and the coefficients of the ATT can be considered as semi-elasticities.

In the following analysis, we separate the employment trends for skilled and unskilled workers in order to see whether the potential skill bias effect of international outsourcing is complementary or substitute with skilled and unskilled labour respectively. On this purpose, Table 6 reports the results for the relative share of white collars only, while Table 7 for blue collars only. Our estimations seem to confirm the unskilled labour-saving nature of production offshoring; while the complementarity with skilled labour is not totally confirmed (coefficients are always positive, but never significantly different from zero).

These results still hold when we finally add the relative share of clerical workers to the relative share of blue collars (Table 8): in this case, however, coefficients are lower than in the blue collars case and the labour substitution effect caused by production offshoring is weaker.

TABLE 5 AROUND HERE

TABLE 6 AROUND HERE

TABLE 7 AROUND HERE

TABLE 8 AROUND HERE

5. Conclusions

In this paper we investigate the effect of offshoring production on the skill mix of manufacturing firms in Italy over the period 1995-2003. Our analysis consists in comparing the demand for skilled relative to unskilled labour by firms that decided to relocate low-skill intensive stages of production to cheap labour (Eastern/Central European) countries in 1998-2000 with the relative demand for skilled labour of a counterfactual sample of firms that did not move their production abroad. In order to control for potential selection bias and for the presence of unobserved factors potentially affecting the offshoring decision, we employ a difference-in-differences propensity score matching estimator: the outcome variable is then calculated as the difference in the relative employment share of skilled workers between the post-treatment period (2001-2003) and the pre-treatment period (1995-1997).

Our estimates point to a "potential" skill bias effect of production offshoring: even if, as expected, the signs of the coefficients for white collars are always positive, they are not significantly different from zero. This results, however, may be due to the limited number of treated units we obtain after cleaning the dataset. When we further separate the relative shares of skilled and unskilled workers, we interestingly find that, while on the one hand offshoring does not seem to enhance the demand for skilled personnel, on the other it contributes to reduce the demand for blue collars. This latter result still holds if we add the share of clerical workers to the share of blue collars.

Our results seem to be in line with previous works (Sachs and Shatz 1994; Strauss-Khan 2003; Piva and Vivarelli 2004; Hijzen, Görg and Hine 2004) that stress how the skill bias effect of international outsourcing is mainly determined by the negative dynamics of the demand for unskilled labour. The will to exploit factor cost differentials and the relocation of low-skill intensive phases of the production process to cheap labour countries has contributed, at least in the short-medium run, to substitute away for domestic employment of manual workers, while keeping the relative share of non manuals relatively stable. However, we also find a partial symptom of a complementarity between offshoring and the employment for high-skilled labour, i.e. the share of high-skilled and low-skilled white collars, but our data do not allow us to draw reliable conclusions about that.

Moreover, the limited number of treated units may play a role in weakening the significance of our estimates, leading us to consider our empirical exercise more like an explorative experiment rather than a representative analysis of the Italian manufacturing industry. On this last purpose, further research is needed.

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Appendix

Table A1. Variables definition

Variable	Definition
Area (dummy)	North West: Liguria, Lombardia, Piemonte, Valle d'Aosta North East: Emilia-Romagna, Friuli Venezia-Giulia, Trentino Alto Adige, Veneto Center: Lazio, Marche, Toscana, Umbria South: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia
Off (dummy)	*Treatment* 1 if the firm offshored at least one phase of the production process to cheap-labour countries (Eastern Europe and former-Yugoslavia), 0 otherwise
ICT (dummy)	*Technology* 1 if the firm has invested in informatics and ICT in the period 1995-97, 0 otherwise
EXPORT (dummy)	*Export activity* 1 if the firm exported goods in 1995-97, 0 otherwise
K/Y	*Capital intensity* Net capital stock over sales
Y/L	*Labour productivity* Net sales per employee
ULC	*Unit labour cost* Labour cost per employee
WC	*White Collars* Managers/Employment + Executives/Employment + Clerks/Employment
BC	*Blue* collars Workmen/Employment
WC/BC	*Skill ratio* White collars over blue collars

Table A2. Summary statistics for the merged sample

Variable	Obs (between)	Overall Mean	Std. Dev.	Min	Max
ICT	184	0.701	0.458	0	1
EXPORT	184	0.712	0.453	0	1
Total Employment	184	83.954	166.760	10	1801
Managers/Employment	184	0.014	0.255	0	0.167
Executives/Employment	184	0.009	0.025	0	0.214
Clerks/Employment	184	0.202	0.122	0	1
K/Y (1995-97)	184	65.647	93.072	0.462	1166.634
Log (K/Y)	184	3.531	1.147	-0.772	7.062
Y/L (1995-97)	184	318.940	426.992	25.118	5567.856
Log (Y/L)	184	5.292	0.885	3.224	8.625
ULC (1995-97)	184	50.699	70.915	6.116	922.069
Log (ULC)	184	3.516	0.753	1.811	6.827
WC	184	0.224	0.130	0	1
Log (WC)	184	-1.656	0.620	-4.883	0
BC	184	0.717	0.142	0	0.985
Log (BC)	184	-0.357	0.235	-1.707	-0.015
WC/BC	184	0.475	0.456	0.002	4.514
Log (WC/BC)	184	-1.044	0.778	-6.265	1.507

Tables and figures

Table 1a. Sample structure (row percentage) by industry and employment classes

Industry (2-digit ATECO 1991)	Small (10-49)	Medium (50-249)	Large (250+)
DB: textile and clothing	54.06	32.43	13.51
DC: leather and footwear	87.50	12.50	0.00
DG: chemicals and allied products	100.00	0.00	0.00
DH: rubber and plastic products	80.00	20.00	0.00
DJ: metal products	70.00	23.33	6.67
DK: industrial machinery	58.33	33.33	8.34

Table 1b. Sample structure by employment classes and geographical area

Employment classes	1995-1997	1998-2000	ISTAT2001	1995-2003 Before cleaning	1995-2003 After cleaning
11-20	21.6	39.94	58.5	14.01	21.74
21-50	41.0	37.14	28.5	37.44	42.39
11-50	*62.6*	*77.08*	*87.0*	*51.45*	*64.13*
51-250	26.5	16.15	11.4	33.82	29.89
251+	10.9	6.78	1.6	14.73	5.98
Geographical area					
North West	40.43	37.54		45.17	47.83
North East	29.57	27.44		29.47	28.26
North	*70.0*	*64.98*	*55.0*	*74.64*	*76.09*
Centre	17.28	16.15	21.0	16.18	16.30
South	12.72	14.40	24.0	9.18	7.61
Total	**4497**	**4680**	**95.017**	**414**	**184**

Table 2. Distribution of firms offshoring production by industry, employment classes and geographical area

Industry (ATECO 1991)	Offshoring	Non offshoring	Total
DB: textile and clothing	1	36	37
DC: leather and footwear	1	7	8
DG: chemicals and allied products	1	1	2
DH: rubber and plastic products	1	14	15
DJ: metal products	2	28	30
DK: industrial machinery	1	35	36
Total	7	177	184
Small (11-49)	4 (0.57)	115 (0.65)	119
Medium (50-249)	1 (0.14)	52 (0.29)	53
Large (+250)	2 (0.29)	10 (0.06)	12
Total	7	177	184
North West	2 (0.29)	86 (0.49)	88
North East	3 (0.43)	49 (0.28)	52
Center	1 (0.14)	29 (0.16)	30
South	1 (0.14)	13 (0.07)	14
Total	7 (0.04)	177 (0.96)	184

Table 3. The structure of offshoring and non offshoring samples

Offshoring

Variable	Obs	Overall Mean	Std. Dev.	Min	Max
ICT	7	0.857	0.354	0	1
EXPORT	7	0.857	0.354	0	1
Total Employment	7	225.667	347.336	16	1163
Managers/Employment	7	0.016	0.023	0	0.08
Executives/Employment	7	0.009	0.025	0	0.12
Clerks/Employment	7	0.171	0.098	0	0.4
K/Y (1995-97)	7	92.936	99.453	12.925	291.659
Log (K/Y)	7	3.898	1.170	2.560	5.676
Y/L (1995-97)	7	445.308	463.571	87.030	1391.964
Log (Y/L)	7	5.550	1.073	4.467	7.238
ULC (1995-97)	7	76.766	75.144	19.460	230.517
Log (ULC)	7	3.947	0.859	2.968	5.440
WC	7	0.196	0.122	0.032	0.48
Log (WC)	7	-1.850	0.734	-3.434	-0.734
BC	7	0.767	0.134	0.44	0.968
Log (BC)	7	-0.284	0.200	-0.821	-0.033
WC/BC	7	0.357	0.315	0.033	1.273
Log (WC/BC)	7	-1.356	0.854	-3.401	0.241

Non offshoring

Variable	Obs	Overall Mean	Std. Dev.	Min	Max
ICT	177	0.695	0.461	0	1
EXPORT	177	0.706	0.456	0	1
Total Employment	177	78.350	153.041	10	1801
Managers/Employment	177	0.014	0.026	0	0.167
Executives/Employment	177	0.009	0.025	0	0.214
Clerks/Employment	177	0.203	0.122	0	1
K/Y (1995-97)	177	64.567	92.746	0.462	1166.634
Log (K/Y)	177	3.517	1.145	-0.772	7.062
Y/L (1995-97)	177	313.942	425.181	25.118	5567.856
Log (Y/L)	177	5.28189	0.877	3.224	8.625
ULC (1995-97)	177	49.668	70.619	6.116	922.069
Log (ULC)	177	3.499	0.744	1.811	6.827
WC	177	0.225	0.130	0	1
Log (WC)	177	-1.648	0.614	-4.883	0
BC	177	0.715	0.142	0	0.985
Log (BC)	177	-0.359	0.236	-1.707	-0.015
WC/BC	177	0.479	0.460	0.002	4.514
Log (WC/BC)	177	-1.032	0.773	-6.265	1.507

Table 4. Testing the difference in the mean propensity score for treated and controls

Test in block 1

Two-sample *t*-test with equal variances

Group	Obs	Mean	Std. Error	Std. Dev.
Controls (0)	295	0.054	0.003	0.043
Treated (1)	18	0.077	0.012	0.051
Combined	313	0.055	0.025	0.044
Difference: mean(0)-mean(1)		-0.023	0.011	
t = -2.2278	Degrees of freedom = 311 H_0: diff = 0			
H_1: diff < 0 $\Pr(T < t) = 0.0133$	H_1: diff ≥ 0 $\Pr(\lvert T\rvert > \lvert t\rvert) = 0.0266$		H_1: diff > 0 $\Pr(T > t) = 0.9867$	
The mean propensity score is not different for treated and controls in block 1				

Test in block 2

Two-sample *t*-test with equal variances

Group	Obs	Mean	Std. Error	Std. Dev.
Controls (0)	4	0.278	0.016	0.032
Treated (1)	3	0.319	0.005	0.009
Combined	7	0.295	0.012	0.032
Difference: mean(0)-mean(1)		-0.041	-0.019	
t = -2.1420	Degrees of freedom = 5 H_0: diff = 0			
H_1: diff < 0 $\Pr(T < t) = 0.0425$	H_1: diff ≥ 0 $\Pr(\lvert T\rvert > \lvert t\rvert) = 0.0851$		H_1: diff > 0 $\Pr(T > t) = 0.9575$	
The mean propensity score is not different for treated and controls in block 2				

Table 5. The effect of production offshoring on skilled labour: white collars/blue collars

Skill ratio	ATT-1	Bootstrap s.e.	ATT-2	Bootstrap s.e.
$WC/BC_{2001/03}$-$WC/BC_{1995/97}$	0.265	0.225	0.408	0.345
WC/BC_{2001}-$WC/BC_{1995/97}$	0.265	0.248	0.429	0.270
WC/BC_{2002}-$WC/BC_{1995/97}$	0.274	0.254	0.390	0.271
WC/BC_{2003}-$WC/BC_{1995/97}$	0.257	0.289	0.408*	0.250

Coefficients with * are significant at 10%; coefficients with ** are significant at 5%.
Notes: ATT-1 refers to first stage estimates of the propensity score in which a logarithmic transformation has been applied to all the continuous variables; ATT-2 refers to first stage estimates of the propensity score in which the continuous variables are taken in levels.
Standard errors are bootstrapped (100 repetitions).

Table 6. The effect of production offshoring on skilled labour: white collars

White collars employment share	ATT-1	Bootstrap s.e.	ATT-2	Bootstrap s.e.
$WC_{2001/03}$-$WC_{1995/97}$	0.145	0.237	0.277	0.190
WC_{2001}-$WC_{1995/97}$	0.169	0.583	0.718	0.548
WC_{2002}-$WC_{1995/97}$	0.175	0.568	0.679*	0.407
WC_{2003}-$WC_{1995/97}$	0.156	0.561	0.691	0.450

Coefficients with * are significant at 10%; coefficients with ** are significant at 5%.
Notes: ATT-1 refers to first stage estimates of the propensity score in which a logarithmic transformation has been applied to all the continuous variables; ATT-2 refers to first stage estimates of the propensity score in which the continuous variables are taken in levels.
Standard errors are bootstrapped (100 repetitions).

Table 7. The effect of production offshoring on unskilled labour: blue collars

Blue collars employment share	ATT-1	Bootstrap s.e.	ATT-2	Bootstrap s.e.
$BC_{2001/03}$-$BC_{1995/97}$	-0.092*	0.048	-0.115**	0.049
BC_{2001}-$BC_{1995/97}$	-0.086*	0.049	-0.110*	0.060
BC_{2002}-$BC_{1995/97}$	-0.094**	0.042	-0.114**	0.053
BC_{2003}-$BC_{1995/97}$	-0.096*	0.053	-0.121**	0.053

Coefficients with * are significant at 10%; coefficients with ** are significant at 5%.
Notes: ATT-1 refers to first stage estimates of the propensity score in which a logarithmic transformation has been applied to all the continuous variables; ATT-2 refers to first stage estimates of the propensity score in which the continuous variables are taken in levels.
Standard errors are bootstrapped (100 repetitions).

Table 8. The effect of production offshoring on unskilled labour: blue collars and clerks

BC + Clerks employment share	ATT-1	Bootstrap s.e.	ATT-2	Bootstrap s.e.
$BCCL_{2001/03}$-$BCCL_{1995/97}$	-0.057*	0.034	-0.051	0.043
$BCCL_{2001}$-$BCCL_{1995/97}$	-0.057*	0.034	-0.051	0.043
$BCCL_{2002}$-$BCCL_{1995/97}$	-0.053*	0.032	-0.047	0.048
$BCCL_{2003}$-$BCCL_{1995/97}$	-0.060*	0.034	-0.055	0.040

Coefficients with * are significant at 10%; coefficients with ** are significant at 5%.
Notes: ATT-1 refers to first stage estimates of the propensity score in which a logarithmic transformation has been applied to all the continuous variables; ATT-2 refers to first stage estimates of the propensity score in which the continuous variables are taken in levels.
Standard errors are bootstrapped (100 repetitions).

Figure 1. Employment trends for treated (offshoring) and untreated firms
(time of assignment into treatment: 1998-2000)