Estimating skills in the Italian manufacturing sector using the INPS Archives: An application to the Italian pattern of trade

G.S.F. Bruno[+], O. Dessy[*], A.M. Falzoni[§ˆ], R. Helg[°ˆ]
[+]Università Bocconi
[*]Università Cattolica, Milano and OPES, Trento
[§]Università di Bergamo
[°] Università Carlo Cattaneo (LIUC)
[ˆ]KITeS, Università Bocconi, Milano

May 11, 2009

Abstract

The aim of this paper is to estimate a new measure of skill for the Italian manufacturing system and to utilize it to characterize some features of the Italian trade pattern. Various approaches have been adopted to measure workers' skill. A first family of measures is based on educational attainment and experience. This family directly measures formal skills, but only imperfectly innate ability. A second family utilizes earnings data on the assumption that the worker is paid the value of its marginal productivity. However, this group of measures only imperfectly measures a worker's skills since it depends also on variables that are specific to the firm such as workers' bargaining power, firm's compensation policies, and rent sharing. For these reasons we exploit the set of information available at the worker and firm level through a new matched-employer-employee panel data (the INPS data-set) so as to decompose the individual wage into an explained, time-varying and time-constant component capturing all persistent characteristics of the worker, purged from confounding firms-specific effects. This is our measure of the skills that workers take from job to job (their portable skills). Based on a three-digit sectoral classification for the Italian manufacturing sector over the years 2000-2002, we average the individual estimates of the latter component -thought of as proxies for individual skills- across workers in the same sector for each year to provide a time-specific and sector-specific measure of the sectoral skill-intensity. This is central to the analysis on the "atypical" specialization pattern of Italy characterized, on one side, by its strength in the so-called traditional sectors and part of the mechanical sector and, on the other side, by its extreme weakness in high tech sectors and in those characterized by scale economies. We utilize our newly constructed measure of skill intensity to analyze the relationship between Italian manufacturing sectors skill intensity and their international trade performance adopting a cross industry approach. Exploiting both the longitudinal and time dimensions of our data, we show that the negative correlation found in cross-section analysis disappears. In fact, in the panel estimates we have the opportunity to control for the effects of all the latent time-constant variables potentially correlated with the skill intensity. A sector technological opportunity variable might play this role: it varies widely across sectors, but it is constant over a short period of time. It is also reasonable to think that technology opportunity and skills intensity are complementary to some degree. Since the Italian pattern of trade is negatively correlated with technological opportunity, not controlling for the effects of this variable is bound to severely underestimate the skill intensity coefficient.

J*EL classification*: F14, F16

Keywords: matched employer-employee data, skill-intensity, international trade performance, sector technological opportunity

1 Introduction

The objective of this empirical application is to estimate a new measure of skill for the Italian manufacturing system and to utilize it to characterize some features of the Italian trade pattern.

Various approaches have been adopted to measure workers' skill. A first family of measures is based on educational attainment and experience. This family directly measures formal skills, but only imperfectly innate ability. A second family utilizes earnings data on the assumption that the worker is paid the value of its marginal productivity. However, this group of measures only imperfectly measures a worker's skills since it depends also on variables that are specific to the firm such as workers' bargaining power, firm's compensation policies, and rent sharing. For these reasons we exploit the set of information available at the worker and firm level through a new matched-employer-employee panel data so as to decompose the individual wage into an explained, time-varying and time-constant component capturing all persistent characteristics of the worker, purged from confounding firms-specific effects. This is our measure of the skills that workers take from job to job, his portable skills.

Based on a three-digit sectoral classification for the Italian manufacturing sector over the years 2000-2002, we average the individual estimates of the latter component -thought of as proxies for individual skills- across workers in the same sector for each year to provide a time-specific and sector-specific measure of the sectoral skill-intensity. This is central to the analysis on the specialization patterns of Italy.

The analysis takes adavantage of the multilevel information (workers/ time/ firm/ sector), available in the INPS matched-employer-employee data-set, in an attempt to purge the individual skill estimates from both firm/sector effects and aggregate transitory effects (see Abowd, Kramarz and Margolis (1999), e.g.).

The paper is organized as follows. The next section contains a description of the data. Section 3 outlines the econometric model and Section 4 presents the empirical results. The skill intensity of the Italian manufacturing industries as emerges from the empirical application is examined in Section 5 and its relationship with the Italian pattern of trade is analyzed in Section 6. Section 7 concludes.

2 Data description

We use two separate sources of data:

- A new matched employer-employee data-set of administrative source, specifically designed for estimating workers skills
- International trade data at the industry-level. These data comes from the United Nations ComTrade-COMEXT database and has been reclassified according the ISIC Rev.3 classification.

For estimating individual skills we use a representative 1:90 sample of administrative data on employees' wages collected by the National Institute of Social Security (Istituto Nazionale di Previdenza Sociale, INPS)[1]. The sample covers the population of workers registered at INPS born on one of the four randomly chosen days of the year. We merge three separate INPS archives: the demographic archive, the employees' archive and the firms' archive. We therefore end up working with a proper 'matched employer-employee data-set'.

The demographic archive contains information at individual level on sex, day and place of birth of individuals. Through an individual code (given by INPS, where the original fiscal code has been anonymised) it is possible to link the demographic archive to the employees' archive, where information on workers' characteristics (such as occupation), work histories and wages is available.

Since 1998 data come from employers' fiscal declarations, and misreporting is prosecuted. In the employees' archive data are not given at the individual level, but for each single contract registered at INPS. Therefore it might happen that the same person for a given year has more than one record within the same firm, or also across different firms. We treat such cases of multiple records for the same workers by selecting only one record at random. A firm identifying code (anonymized by INPS) is available for each record, so that it is possible to link the employees' archive to the firms' archive, supplementing the data-set with information on the size of the firm, its date of birth/death, localization and sector of activity.

The INPS data do not cover self-employment and public employment but only the private sector excluding agriculture. Consistently with our research goals, we further restic the analysist to the manufacturing sector. The original information on sectors in the INPS data is given through an internal code (Codice Statistico-Contributivo, CSC). Fortunately, INPS offers also a conversion to ATECO81 codes. However, since we need to merge estimation results

[1] In particular, we use INPS data available at Bocconi University.

from the INPS data-set to the international trade data at sector levels available under the ISIC classification, we have re-aggregated ATECO81 codes into ISIC codes.

Although the employees' archive covers the 1985 - 2004 period, we can base our empirical analysis only upon the time span 2000 - 2002 since a) firms' data are available only over the period 1998 through 2002 and b) years 1998 and 1999 are affected by severe reporting errors for the wage variables.

3 The model

The dependent variable y_{it} in our estimating wage equation is a measure of the average daily wage of worker $i = 1, ..., N$ at year $t = 1, ..., T_i$. More specifically, y_{it} stands for the logarithm of the ratio of the current compensation to the number of actual days worked by worker i in year t.

The explanatory variables are the components of the column vector $x_{i,t}$: total experience measured as the number of years of work as of time t; sectoral experience measured as the number of years of work in the same sector as of time t; firm tenure measured as the number of years of work in the same firm as of time t; a part-time/full-time dummy, alone and interaced with a dummy indicating if the worker is not born in Italy; the dimension (number of employees) of the firm where the worker is employed at time t (logarithms); occupation dummies (blue collars, white collars, professional and managerial staff, blue-collar and white collar apprentices, other) and time dummies.

3.1 Estimation samples

The INPS archive allows the researcher to pursue two sampling strategies. Following the first strategy, only the employees that work in only one firm at the time are sampled. In this case the estimating equation is as follows

$$y_{it} = \alpha_i + \eta_{j(i,t)} + x_{it}^T \beta + \epsilon_{it},\ t = 1, ..., T_i,\ i = 1, ..., N \tag{1}$$

with $j(i,t)$ indicating the firm $j = 1, ..., J$ where worker i is employed at time t.

The second strategy preserves the cases of employees working for different firms at the same time, so that the estimating equation is given by:

$$y_{ijt} = \alpha_i + \eta_j + x_{ijt}^T \beta + \epsilon_{ijt},\ t = 1, ..., T_i,\ i = 1, ..., N,\ j = 1, ..., J$$

The latter data-set would ensure greater chance for identification of the fixed effects. A firm effect could in fact be identified also for a firm with no turn-over, using information from only one cross-section t, provided that the firm employs more than one worker at time t. Similarly, a worker's effect could be identified also for a stayer provided that he or she works in more than one firm at time t. This strategy, however, is computationally troublesome, so we have decided to focus only on the restricted sample of single-firm workers and use model (1).

3.2 The wage equation

A standard least square dummy variable estimator (LSDV) with worker and firm dummies would provide a robust estimation method for model (1). If the number of firms J is large, however, the LSDV is difficult to implement, involving the brute-force numerical inversion of a large, unpatterned cross-product matrix. Since J in our data is a large number, to estimate individual fixed effects α_i we adopt an approximate model with a 3-digit sector effect $\theta_{s[j(i,t)]}$ and firm group-means of the regressors $\overline{x}_{j(i,t)}$ replacing η_j

$$y_{it} = \alpha_i + \theta_{s[j(i,t)]} + \lambda \overline{x}_{j(i,t)} + x_{it}^T \beta + \epsilon_{it},\ t = 1, ..., T_i,\ \ i = 1, ..., N \qquad (2)$$

with $s[j(i,t)]$ indicating the 3-digit sector $s = 1, ..., S$ where worker i works at time t.

For identification it is assumed that all explanatory variables are strictly exogenous, that is

$$E\left(\epsilon_{it} | x_{i1}, ..., x_{iT_i}, \alpha_i, \theta_{s[j(i,1)]}, ..., \theta_{s[j(i,T_i)]}\right) = 0 \qquad (3)$$

This is a strong assumption that may be relaxed in future developments of the analysis.

Model (2) is applied to the whole sample of single-firm workers and to the subsample of males. Standard errors estimates are robust to arbitrary heteroskedasticity and within-group serial correlation.

3.3 Estimated sectoral skill intensity

Let $\widehat{\beta}$, $\widehat{\lambda}$ and $\widehat{\theta}_{s[j(i,t)]}$ denote the LSDV estimates for β, λ and $\theta_{s[j(i,t)]}$, respectively. Then, the estimated latent skill component $\widehat{\alpha}_i$ is given by

$$\widehat{\alpha}_i = \overline{y}_i - \left(\widehat{\theta}_{s[j(i,t)]} + \widehat{\lambda}\overline{x}_{j(i,t)} + \overline{x}_i^T \widehat{\beta}\right)$$

where $\overline{y}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} y_{it}$ and $\overline{x}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} x_{it}$.

Averaging $\widehat{\alpha}_i$ across all individuals gives the estimated average skill in the sample, $\overline{\alpha} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\alpha}_i$. Therefore, the individual skill component can be also expressed as the residual from $\overline{\alpha}$, $\widehat{\delta}_i = \widehat{\alpha}_i - \overline{\alpha}$.

We obtain our desired measure of sectoral skill intensity, $\widehat{\delta}_s$, by averaging $\widehat{\delta}_i$ across all workers in sector s. Define the set of all individuals working in sector s as

$$\mathfrak{S}_s = [i = 1, ..., N : s[j(i,t)] = s]$$

and let N_s denote the size of $\mathfrak{S}_s$, so

$$\widehat{\delta}_s = \frac{1}{N_s}\sum_{i \in \mathfrak{S}_s} \widehat{\delta}_i \qquad (4)$$

Under hypothesis (3) $\widehat{\delta}_s$ is unbiased and consistent for N_s large. A N_s-consistent estimate for the standard error of $\widehat{\delta}_s$ is

$$\widehat{\delta}_s = \frac{1}{N_s}\sqrt{\sum_{i\in\mathfrak{S}_s}\left(\widehat{\delta}_i - \widehat{\delta}_s\right)^2}.$$

Notice that $\widehat{\delta}_s$ takes on negative values when

$$\frac{1}{N_s}\sum_{i\in\mathfrak{S}_s}\widehat{\alpha}_i < \overline{\alpha}$$

that is when the implicit sectoral skill estimate is below average. Clearly, the ranking of sectors is invariant to whether $\frac{1}{N_s}\sum_{i\in\mathfrak{S}_s}\widehat{\alpha}_i$ or $\widehat{\delta}_s$ is used as the ranking variable. Nonetheless, we would rather use $\widehat{\delta}_s$ as it also partitions sectors into above and below-average sectors.

4 Results

4.1 Estimates

Estimation results are reported in Table 4.1. Sectoral dummies and variables in firm-group-means are jointly significant indicating that firm-specific effects are an important component of the employee compensation. All estimated coefficients are plausible in sign and size. The estimated coefficient on the part-time dummy indicates that upgrading from part-time to full-time rewards the employee of a 31% wage increase. Interestingly, the full-time premium is higher for foreign workers amounting to 50%. This emerges from an estimate of 0.19 for the coefficient on the foreign/part-time interaction variable. The size of the estimated coefficients on the seven occupation dummies fully reflect their skill content, so that the highest coefficients are those on executives and white-collars and the lowest are those on blue-collars and apprentices. While firm tenure is not significant, sectoral experience turns out as only marginally significant and with a vary low coefficient, which may be due to poor identification in the presence of a full set of time indicators. These, on the other hand, are jointly significant. Firm size and squared firm size are not significant.

4.2 Specification tests

The question arises about the validity of the specification (2), choosen for approximating equation (1). We test specification (2) through a robust Hausman test strategy, along the following lines.

Model (2) turns out to be a restriction of the following general specification

$$y_{it} = \gamma_{i,j(i,t)} + x_{it}^T\beta + \epsilon_{it},\ t = 1,...,T_i,\ i = 1,...,N \tag{5}$$

where $\gamma_{i,j(i,t)}$ stands for a time-constant employer-employee group effect, that is a latent variable fixed over time but varying across firms and employees. The implicit constraint at work in model (2) is

$$\gamma_{i,j(i,t)} = \alpha_i + \lambda \overline{x}_{j(i,t)} + \theta_{s[j(i,t)]}, \; i = 1, ..., N, \; t = 1, ..., T_i \tag{6}$$

If (6) holds then the LSDV estimator applied to equation (2), $\widehat{\beta}$, is both consistent and efficient, on the other hand if (6) does not hold, then $\widehat{\beta}$ is not consistent. To the opposite, the LSDV estimator applied to (5), $\widehat{\beta}^*$, is consistent whether or not (6) hold. Therefore, an Hausman test based on the difference between the two estimators can be carried out to evaluate model (2)

$$H = \left(\widehat{\beta} - \widehat{\beta}^*\right)' Var\left(\widehat{\beta} - \widehat{\beta}^*\right)^{-1}\left(\widehat{\beta} - \widehat{\beta}^*\right) \sim \chi^2(k) \tag{7}$$

Indeed, if model (2) is not rejected against model (5) it is all the more so against model (1), which emerges as a particular case of model (5). The reason why we use (5) instead of (1) as the alternative hypothesis of the Hausman test is that the former is computationally inexpensive, being easily implemented via the standard fixed effect procedures available in most econometric packages. The Hausman statistics (7) is constructed using the cluster estimator of the variance-covariance matrix $Var\left(\widehat{\beta} - \widehat{\beta}^*\right)$ suggested by Arellano (1987), which is robust to arbitrary heteroskedasticity and within-group serial correlation (through the `suest` Stata command).

The test does not reject the null (6) at any conventional significance level: $\chi^2(17) = 24.56$, $p - value = 0.105$. Hence, not including pure firm-effects in the estimating wage equation does not seem to harm the model specification.

5 The skill intensity of Italian manufacturing industries

Table 5.1 shows the skill intensity of the Italian manufacturing industries emerging from the sectoral skills estimates obtained in the previous section. The four-digit manufacturing sectors are ranked from the highest to the lowest according to the estimated proxies for the skill intensity as in equation (4).

At the top of the ranking, we find sector 1532 (Manufacture of starches and starch products), followed by sectors 2211 (Publishing of books, brochures, musical books and other publications), 3330 (Manufacture of watches and clocks), and 2430 (Manufacture of man-made fibres). At the bottom, the most unskilled-intensive sectors are: 2023 (Manufacture of wooden containers), 1513 (Processing and preserving of fruit and vegetables), and 1920 (Manufacture of footwear)[2].

Going through the skill-intensity ranking, a lot af sectoral heterogeneity emerges, often across four-digit sectors within the same two-digit industry. This

[2]For a description of the ISIC Rev.3 four-digit manufacturing sectors, see Appendix A.

can be easily seen by grouping the four-digit sectors into 4 main categories according to the magnitude of the deviation from the average estimated skill-intensity of the manufacturing industry as a whole. We distinguish 4 categories: very high skill intensive sectors (VH, with deviations $> +0.1$); high skill intensive sectors (H, with deviations between 0 and $+0.1$), low skill intensive sectors (L, with deviations between 0 and -0.1); very low skill intensive sectors (VL, with deviations $>$ -0.1) (Table 5.1). Apart from industries in which there is a single four-digit sector, only in two cases all the activities of a given production group may be classified into the same skill category. The two cases, both classified in the very low skill category, are the 1810 and 1820 sectors of the two digit industry 18 (Manufacture of wearing apparel; dressing and dyeing of fur) and the 1911, 1912 and 1920 sectors of the two digit industry 19 (Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear).

Thanks to our highly disaggregated - four digit - sectoral classification, we can show how activities within the same production group are characterized by very different skill intensity. As a first step, we can look at the two digit sectoral groups to see whether, in each group, all the four digit activities are ranked as skilled or unskilled or if there are groups with a mix of both. Table 5.2 shows that, out of 24 two digit sectoral groups, 12 are definitely skill intensive, only 4 are definitely unskilled and 8 embody either skilled and unskilled activities. In this last group, we find industries usually classified as low-technology, such as the 15 - Manufacture of food and beverages, the 17 - Manufacture of textiles, the 20 - Manufacture of wood and of products of wood and cork, except furniture, the 21 - Manufacture of paper and paper products, and so on. In the case of the food and beverage industry for example, the four digit activities are spread along all the ranking, showing a very heterogeneous degree of skill intensity. On the one hand, there are activities such as the 1552 – Manufacture of wines and the 1553 – Manufacture of malt liquors and malt, belonging to the very high skill intensive category; on the other hand, there are sectors such as the production, processing and preserving of meat, fish, vegetables, etc., where simple and routine activities prevail, belonging to the very low skill intensive category.

Even in the case of two digit industries unambiguously skill intensive (that is with all the four digit sectors placed in the positive part of the ranking), may be interesting to see whether and how the activities are characterized by different degree of skill intensity. Within the "Other transport equipment industry" (ISIC 35), for example, the production of railway locomotives (3520) shows a higher skill intensity than that of aircrafts (3530), a production generally classified as very high-tech.

Comparing our ranking with other classifications based on the skill intensity of the sectors, some interesting peculiarities emerge. Table 5.2 shows a classification by type of occupation based on data on the ratio of white and blue collars workers from ISTAT, "Conti economici delle imprese", and a classification by educational attainment (European Commission, 2003). In some cases, such as the "Manufacture of motor vehicles" (ISIC 34) or the "Manufacture of basic metal" (ISIC 27), our estimated skill intensity classifies the 2-digit sectors as unambiguously skill intensive whereas the other two classifications place these sectors in the low skilled group.

6 An application: the skill intensity of the Italian trade pattern

We analyze the relationship between the Italian pattern of trade and the skill intensity of its industries.

The Italian pattern of trade is measured by the Index of Specialization (ISP) sometimes called the index of revealed comparative advantages, which, for a sector, meausures its weight on Italian manufacturing exports divided by its weight on World manufacturing exports .

The Italian pattern of trade is characterized, on one side, by its strength in the so-called traditional sectors and part of the mechanical sector and, on the other side, by its extreme weakness in high tech sectors and in those characterized by scale economies.

This stylized fact of the Italian economy emerges from the various analysis based on the clustering of industries into groups with common features related to technology or input use (OECD, 1997; O'Mahony and Van Ark, 2003; IMF, 2007; Pavitt, 1984). An example is presented in Table 6.1. The specialisation index in this case is based on value added data and the sectoral taxonomy adopted by the European Commission is based on labour skills. The Italian economy is the only advanced and big EU country that shows strong specialisation in low skilled intensive sectors (an index bigger than one denote specialisation). For the Italian economy value added, production and export specialisation exhibit the same features.

Instead of arbitrarily clustering industrial sectors according to input use, an alternative and more general approach ("cross industry approach") is to study the relationship between the chosen measure of industrial specialisation and a measure of factor intensity. However, also studies that have followed this approach have reached the same conclusion of the taxonomical approach: adopting regression analysis, the estimated coefficient of the skill intensity variable is negative and significant (for example, Helg-Onida, 1984; Helg, 1989; Romalis, 2004).

One problem of the previous analysis is the measure of skill intensity adopted to classify sectors in different categories or adopted as an independent variable in regression analysis. Typical measures based on educational attainments, employment status or wage level are, as already stressed in previous sections, highly imperfect measures.

In this final part of the paper, we utilize our newly constructed measure of skill intensity to analyze the relationship between Italian manufacturing sectors skill intensity and their international trade performance adopting a cross industry approach.

On the theoretical side, this framework of empirical analysis could be linked to the factor proportions approach to international trade. It is well recognized by now that this kind of empirical analysis is only loosely linked to the Heckscher-Ohlin theorem of international trade and cannot be considered an empirical test of its predictions (Leamer, 1980). The loose link comes from the utilization in the empirical analysis of two out of the three basic elements of the theorem: measure of trade performance and measure of factor intensities, leaving out factor endowmwnts. However, Romalis (2004) has redeemed this framework of empirical analysis showing that it can be utilized to test a quasi Heckscher-Ohlin (HO) prediction. Using a version of the HO model with a continuum of goods and introducing monopolistic competition and transport costs he obtains the following proposition: "Countries capture larger shares of world production and trade in commodities that more intensively use their abundant factor". This is the theoretical background for our empirical analysis.

The estimated equation is of this type:

$$ISP_i = \alpha + \beta Skill_i + \delta Capital_i + \epsilon_i$$

The measure of capital intensity is investment per employee. The source of our data are: for ISP the Comext database and for Capital the Istat's Conti Economici delle Imprese database for year 2003. The analysis is conducted with 89 sectors.

Table 6.2 shows the standard cross industry regression for Italy. The coefficient of skill intensity is significantly negative while that of capital intensity is not significantly different from zero. The adoption of a more precise measure of skill intensity doesn't change the picture: Italian sectors with better international performance are characterized by low skill intensity.

One should refrain to interpret this result as implying that in Italy a reduction in the skill intensity of a sector should improve international performance. Such a conclusion is not warranted by our longitudinal analysis. Such an interpretation requires an analysis that takes into account also the time dimension. For this reason we change the characteristics of our approach and exploit both the longitudinal and time dimensions with a panel data set. This is made up by 89 industrial sectors for three years (2000, 2001 and 2003). We eliminate the capital variable since, at this stage, it has been recorded only for one year (the Skill variable remains negatively significant if from the cross industry regression in Table 6.2 we eliminate Capital. This result together with the lack of significance of the Capital variable make us confident that the unavailability of data for Capital in the time dimension is not a major problem).

The new regression equation is

$$ISP_{it} = \alpha_i + \beta Skill_{it} + \epsilon_{it}$$

We exploit the panel nature of this database to control for all the omitted variables (measurable and non measurable) potentially correlated with the skill intensity variable that are constant over time, but varies across sectors (i.e. we try to overcome a potential omitted variable bias). In the specification we allow for industry fixed effects, α_i.

Results are presented in Table 6.3. In eq 8, within estimates show a positive and significant coefficient for the skill intensity variable.

What has happened? In these new estimates we have controlled for the effects of many omitted variables potentially correlated with Skill. A sector technological opportunity might play this role: it varies widely across sectors, but it is constant over a short period of time. It is also reasonable to think that technology opportunity and skills intensity have a certain degree of complementarity. Since the Italian pattern of trade is negatively correlated with technological opportunity (on average, in Italy sectors characterized by high technological opportunities have a weak relative export performance), not controlling for the effects of this variable we would obtain a downward biased estimate of the Skill coefficient. Indeed, this was the case of the results in Table 6.2. And is also the case for the results presented in Table 6.4 eq. 9, where we still utilize the panel database but don't allow for fixed effects.

As a final check in the following Figure 6.1 we produce the component-plus-residual plot as a diagnostic check for the linearity assumption we have made. A median spline of the plotted points has been also superimposed. The plot supports the linearity assumption.

7 Conclusions

This paper adopts matched employer-emplyees data methods to estimate the sectoral skill intensity of the Italian manufacturing industr and to investigate the specialization patterns of Italy.

The empirical analysis goes through two steps. In the first step we use a general wage equation with workers dummies and a number of firm-specific variables to obtain workers skill estimates, purged by possibly correlated latent firm-effects. The workers skill estimates are then averaged over all workers within the same sector/year cell to obtain a sector/year specific measure of sectoral skill intensity. An important finding at this level of analysis, obtained by looking through the estimated sectoral skill intensity, is that a lot af sectoral heterogeneity emerges, often across four-digit sectors within the same two-digit industry.

The second step uses regression analysis to unveil the sign of the correlation between the sectoral trade performance and the sectoral skill intensity variable obtained in the first step. The cross-section regression confirms the traditional story for the pattern of specialisation of Italy, that is Italian sectors with better international performance are characterized by low skill intensity. The picture changes completely, though, when the panel data is used. This endows the data with a time dimension, so that possibly correlated sectoral fixed effects are identified. Results from the general model indicate a significantly positive sign for the sectoral trade performance/sectoral skill intensity correlation, which is evidence of a downward bias in the cross-section estimates. We conjecture that the sectoral fixed effects in the general model mostly capture the impact of sectoral technological opportunity, which, while positively correlated to the sector skill intensity, for Italy is also known to be negatively correlated to the sector export performance on average.

References

[1] Abowd, J., Kramarz, F. and D. Margolis. "High Wage Workers and High Wage Firms," Econometrica, July 1999.

[2] Arellano, M., 1987, "Computing Robust Standard Errors for Within-Groups Estimators," Oxford Bulletin of Economics and Statistic 49.

[3] European Commission (2003), EU productivity and competitiveness: An industry perspective. Can Europe resume the catching-up process?, Mary O'Mahony and Bart van Ark (ed.).

[4] EU (2007), EU Industrial Structure 2007, DG Enterprise and Industry. EU Commission

[5] Helg R. (1989), Specializzazione internazionale e caratteristiche industriali: un approfondimento, in Onida F. (a cura di), Specializzazione e integrazione internazionale dell'industria italiana, Vol.I, F.Angeli, Milano, 1989.

[6] Helg R., F. Onida (1984), Specializzazione internazionale e caratteristiche dell'offerta: un'analisi econometrica sull'industria manifatturiera italiana negli anni '70, (con F.Onida), in V.A., Ricerche quantitative per la politica economica, Banca d'Italia, numero speciale dei Contributi alla Ricerca Economica 1984.

[7] IMF (2007), World Economic Outlook, April, Chapter 5.

[8] ISTAT (various years), Conti economici delle imprese, Rome.

[9] Leamer, Edward E. (1980), "The Leontief Paradox Reconsidered," Journal of Political Economy, June, 88, 495-503.

[10] OECD, (1997), Science, Technology and Industry Scoreboard. OECD Paris.

[11] O'Mahony and Van Ark (2003), EU productivity and competitiveness: an industry perspective, European Commission, 2003.

[12] Pavitt, K. (1984), Sectoral patterns of technical cahnge: Towards and taxonomy and a theory. Research Policy, 13, 343-373.

[13] Romalis, J., (2004), "Factor Proportions and the Structure of Commodity Trade," American Economic Review, Vol. 94 (No. 1), pp. 67-97.

Table 2.1 - Employees' & firms' characteristics in matched sample

	2000	2001	2002	Average
N. Individuals	28130	28571	27745	28148.67
% male	67.77	68.09	67.85	67.90
Occupation (%)				
Executives	2.15	2.06	2.23	2.15
Managers	2.79	2.93	3	2.91
White collars	33.89	34.03	35.59	34.50
Blue collars	52.4	52.6	51.1	52.03
Apprentices	6.78	6.45	6.22	6.48
Apprentices/White collars	0.12	0.1	0.13	0.12
Apprentices/Blue collars	0.02	0.02	0.04	0.03
Others (pilots, outworkers,	1.85	1.8	1.69	1.78
middlemen, teach., journ.)				
N. Firms	20512	20904	20494	20636.67

Table 4.1 - Results : fixed - effects regression

Dep. Variable: lcomp_gior	Coef.	Robust Std. Error	t	p-value	[95% Conf. Interval]	
sex-experience	-0.0003634	0.0020155	-0.18	0.857	-0.0043138	0.0035869
sector-tenure	0.0008622	0.000513	1.68	0.093*	-0.0001433	0.0018677
pftime1	0.3068107	0.0310954	9.87	0.000**	0.2458632	0.3677582
cbirth(flag)-pft	0.1882173	0.086944	2.16	0.030**	0.0178058	0.3586289
ldim	0.0209284	0.0163812	1.28	0.201	-0.011179	.0530359
docc-executives	0.2294747	0.0554422	4.14	0.000**	0.1208071	0.3381422
docc-managers	0.0505412	0.0434845	1.16	0.245	-0.0346892	0.1357715
docc-blue collar	-0.0213714	0.0417263	-0.51	0.609	-0.1031556	0.0604128
docc-white collar	0.0072651	0.0419321	0.17	0.862	-0.0749225	0.0894527
docc-appr.	-0.2066792	0.0385561	-5.36	0.000**	-0.2822498	-0.131109
docc-appr./wh.c.	-0.0153184	0.0439519	-0.35	0.727	-0.1014648	0.0708281
docc-appr./bl.c.	(dropped)					
docc-others	0.055229	0.0548719	1.01	0.314	-0.0523208	0.1627787

R^2 within = 0.1275
R^2 between = 0.1774
R^2 overall = 0.1956
F(124,45985) = 128089.24
Prob > **F**= 0.0000

(Std. Err. adjusted for 45986 clusters in id)
**sign.5%,*sign.10%

TABLE 5.1 - The skill intensity of Italian manufacturing industries

ISIC Rev. 3 Code	No. Obs.	Sectoral Mean	Std. dev. (1)	Std. dev.(2)	Skill intensity groups
1532	20	0,5324417	0,0967543	0,4326982	VH
2211	980	0,386112	0,0164863	0,5161033	VH
3330	12	0,3368005	0,1358415	0,4705687	VH
2430	91	0,3265676	0,0321993	0,3071616	VH
3599	22	0,3012067	0,1050943	0,4929359	VH
1552	231	0,2861512	0,0231316	0,3515697	VH
2423	1536	0,2838632	0,0098592	0,3864009	VH
2422	308	0,2564711	0,0229297	0,4024146	VH
2411	1443	0,2526495	0,0105886	0,4022275	VH
1553	50	0,2492766	0,0450272	0,3183907	VH
3520	119	0,2385305	0,0326698	0,356385	VH
1429	22	0,2146697	0,041929	0,1966645	VH
3000	4237	0,2082705	0,0067697	0,4406559	VH
3313	1660	0,1934579	0,0127132	0,5179755	VH
1531	186	0,1851872	0,0315413	0,4301659	VH
2925	1824	0,1843029	0,0100777	0,4304	VH
3410	640	0,1681439	0,0164055	0,4150287	VH
1200	14	0,1653016	0,0797708	0,2984748	VH
2922	1238	0,1508273	0,0110176	0,3876579	VH
2924	843	0,1356198	0,014616	0,4243678	VH
2921	503	0,1352647	0,0162945	0,3654466	VH
2811	238	0,1292848	0,0237344	0,3661565	VH
1310	9	0,1283746	0,1394612	0,4183835	VH
3320	162	0,1281796	0,0362914	0,4619144	VH
2421	770	0,128069	0,0153774	0,4267068	VH
3150	545	0,1235356	0,0199063	0,4647183	VH
1422	35	0,1200822	0,0460927	0,2726879	VH
2812	197	0,1168261	0,0273076	0,3832805	VH
2710	1654	0,1135736	0,0099451	0,404461	VH
3530	448	0,1132278	0,0159376	0,3373363	VH
2910	2740	0,1068216	0,0075257	0,3939312	VH
3591	218	0,1020622	0,0266613	0,3936501	VH
3140	1954	0,0955564	0,009762	0,4315187	H
2511	860	0,0813473	0,0148144	0,4344437	H
1549	696	0,0791569	0,0155359	0,4098655	H
3110	1352	0,0781818	0,0106513	0,391644	H
3420	373	0,0776521	0,0195316	0,3772187	H
3220	1200	0,0756807	0,0128228	0,4441933	H
2221	1919	0,0688505	0,0089017	0,3899505	H
3430	618	0,0546547	0,0154726	0,3846431	H
2927	3110	0,0481554	0,0091716	0,5114749	H
2021	166	0,0460364	0,0318175	0,4099404	H
3130	188	0,0385984	0,0334059	0,4580388	H
2424	399	0,0376519	0,0237705	0,474815	H
2720	464	0,0374102	0,0163323	0,3518084	H
2694	248	0,0340711	0,0196384	0,3092659	H
2930	551	0,0335385	0,0182693	0,4288418	H
3312	436	0,033349	0,020618	0,430516	H
2699	30	0,0304398	0,0589213	0,322725	H

2010	235	0,0289414	0,0236286	0,3622198	H
2429	122	0,0269402	0,0332035	0,366745	H
2610	758	0,025932	0,0132729	0,3654258	H
3511	360	0,0230698	0,0214587	0,4071507	H
1712	549	0,015558	0,0199113	0,4665358	H
2101	362	0,0102735	0,0216053	0,4110692	H
1711	2260	0,0096919	0,0095331	0,4531994	H
1554	240	0,0034731	0,0257641	0,3991361	H
1520	623	-0,0057596	0,0175011	0,4368257	L
2899	7061	-0,0082626	0,0053212	0,4471398	L
2520	2543	-0,0091593	0,0080083	0,4038446	L
1514	263	-0,0190209	0,0193169	0,3132671	L
2695	878	-0,0277574	0,0117894	0,3493322	L
2893	4901	-0,0343946	0,005805	0,40639	L
2691	957	-0,034699	0,0154492	0,4779269	L
2891	1269	-0,0357961	0,0123231	0,4389871	L
1551	104	-0,0389469	0,0466721	0,4759637	L
3692	40	-0,0392609	0,044272	0,280001	L
2102	959	-0,0453699	0,012313	0,3813062	L
2693	191	-0,0521643	0,0254845	0,3522033	L
1511	665	-0,0742056	0,0164323	0,4237491	L
1722	51	-0,094429	0,0413755	0,2954805	L
1600	44	-0,0965334	0,0449903	0,2984318	L
1512	96	-0,0988111	0,0349357	0,3422984	L
3691	27	-0,1040669	0,0836468	0,4346413	VL
2696	748	-0,1333621	0,0109504	0,2994886	VL
1544	446	-0,1356889	0,0294958	0,6229128	VL
3610	2401	-0,1366473	0,0077717	0,3808143	VL
1410	392	-0,1505602	0,0159777	0,3163427	VL
1542	105	-0,1706061	0,0231255	0,2369656	VL
1911	550	-0,1742096	0,0181831	0,4264318	VL
1533	197	-0,1789664	0,030406	0,4267684	VL
1541	2246	-0,2105201	0,0072968	0,3458082	VL
2022	1478	-0,2421631	0,0094258	0,3623737	VL
2029	377	-0,2466741	0,0170334	0,3307295	VL
1543	413	-0,2597458	0,0200333	0,4071239	VL
1912	713	-0,2653133	0,0153054	0,4086859	VL
1810	4944	-0,2750707	0,005511	0,3875	VL
1730	1420	-0,2780764	0,0108463	0,4087212	VL
1820	90	-0,2969929	0,026076	0,247379	VL
1920	1987	-0,3294664	0,0081067	0,3613607	VL
1513	999	-0,3715032	0,0094467	0,2985829	VL
2023	183	-0,4011116	0,0243589	0,3295206	VL

(1) std. dev. from sectoral average i.e. (2)/sqrt (No. of observations)
(2) skills std. dev. within each industry

Table 5.2 – The sectoral skill intensity

ISIC Rev. 3 Code		Estimated skill intensity (1)	ISTAT Classification by type of occupation (2)	EC (2003) Classification by educational attainment (3)
12	Mining of uranium and thorium ores	**+**	n.a.	LS
13	Mining of metal ores	**+**	n.a.	LS
14	Other mining and quarrying	**+/-**	n.a.	LS
15	Manufacture of food and beverages	**+/-**	UN	LS
16	Manufacture of tobacco	**-**	UN	LS
17	Manufacture of textiles	**+/-**	UN	LS
18	Manufacture of wearing apparel; dressing and dyeing of fur	**-**	UN	LS
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	**-**	UN	LS
20	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	**+/-**	UN	LIS
21	Manufacture of paper and paper products	**+/-**	UN	LIS
22	Publishing, printing and reproduction of recorded media	**+**	S	LIS
23	Manufacture of coke, refined petroleum products and nuclear fuel	n.a.	S	HS
24	Manufacture of chemicals and chemical products	**+**	S	HS
25	Manufacture of rubber and plastic products	**+/-**	UN	LS
26	Manufacture of other non-metallic mineral products	**+/-**	UN	LS
27	Manufacture of basic metals	**+**	UN	LS
28	Manufacture of fabricated metal products, except machinery and equipment	**+/-**	UN	LIS
29	Manufacture of machinery and equipment, nec	**+**	S	LIS
30	Manufacture of office, accounting and computing machinery	**+**	S	HS
31	Manufacture of electrical machinery and apparatus, nec	**+**	S	LIS
32	Manufacture of radio, television and communication equipment and apparatus	**+**	S	HS
33	Manufacture of medical, precision and optical instruments, watches and clocks	**+**	S	HIS
34	Manufacture of motor vehicles, trailers and semi-trailers	**+**	UN	LS
35	Manufacture of other transport equipment	**+**	S	HIS
36	Manufacture of furniture; manufacturing, nec	**-**	UN	LS
37	Treatment and preparation for recycling	n.a.	UN	LS

(1) Positive or negative signs indicate a skill intensity above or below the average manufacturing skill intensity for the sectors at the 4 digit level.

(2) Ratio of white/blue collars in Italian manufacturing. UN=below the average manufacturing ratio; S=above the average manufacturing ratio
(3) EC (2007). HS=High Skilled; HIS= High Intermediate Skilled; LIS= Low Intermediate Skilled; LS=Low Skilled

Table 6.1 – Sector specialisation index by labour skills categories (average 2001-2003)

Country	High	High-intermediate	Low-intermediate	Low
AT	0.87	0.89	1.22	1.07
BE	1.12	1.04	0.96	0.76
CZ	0.73	1.00	1.24	1.25
DE	1.03	0.99	0.99	0.95
DK	0.93	1.19	1.04	0.92
EE	0.81	1.12	1.13	1.13
ES	0.83	0.83	1.10	1.39
FI	0.90	1.13	1.22	0.80
FR	1.12	1.06	0.88	0.86
GR	0.86	0.79	1.06	1.41
HU	1.00	0.93	0.99	1.08
IE	1.13	0.92	0.96	0.85
IT	0.99	0.84	1.04	1.11
LT	0.68	1.13	1.21	1.27
LU	1.28	0.94	0.84	0.68
LV	0.80	1.13	1.26	0.94
MT	0.90	1.21	0.79	1.35
NL	1.02	1.05	1.00	0.91
PL	0.77	0.79	1.33	1.20
PT	0.90	1.01	1.03	1.16
SE	0.95	1.30	1.03	0.81
SI	0.91	0.84	1.15	1.12
SK	0.81	1.00	1.15	1.21
UK	1.02	1.07	0.94	0.97

Source: EC (2007)

Table 6.2 - Cross industry regression- 2003

```
. regress isp_inps2003 skill_isicy2002  invdip03, vce(robust) beta depname(ISP200
> 3)

Linear regression                                      Number of obs =      85
                                                       F(  2,    82) =    2.72
                                                       Prob > F      =  0.0716
                                                       R-squared     =  0.0595
                                                       Root MSE      =  1.5224

------------------------------------------------------------------------------
             |               Robust
     ISP2003 |      Coef.   Std. Err.      t    P>|t|                     Beta
-------------+----------------------------------------------------------------
skill_i~2002 |  -2.021711   1.023428    -1.98   0.052                -.2317357
    invdip03 |  -.0083722   .0112094    -0.75   0.457                -.0481115
       _cons |   1.630175   .1669612     9.76   0.000                        .
------------------------------------------------------------------------------
```

Table 6.3 - Panel regression: within estimator (controlling for industry effects)

```
. xtreg   isp_inps skill_isicy, fe robust

Fixed-effects (within) regression               Number of obs      =       267
Group variable: isic                            Number of groups   =        89

R-sq:  within  = 0.0476                         Obs per group: min =         3
       between = 0.0449                                        avg =       3.0
       overall = 0.0401                                        max =         3

                                                F(1,177)           =      4.68
corr(u_i, Xb)  = -0.2441                        Prob > F           =    0.0318

                                  (Std. Err. adjusted for clustering on isic)
------------------------------------------------------------------------------
             |               Robust
    isp_inps |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 skill_isicy |   .4078433   .1884793     2.16   0.032     .0358875    .7797992
       _cons |     1.5064   .0077315   194.84   0.000     1.491142    1.521658
-------------+----------------------------------------------------------------
     sigma_u |  1.6576095
     sigma_e |  .11233792
         rho |  .99542808   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

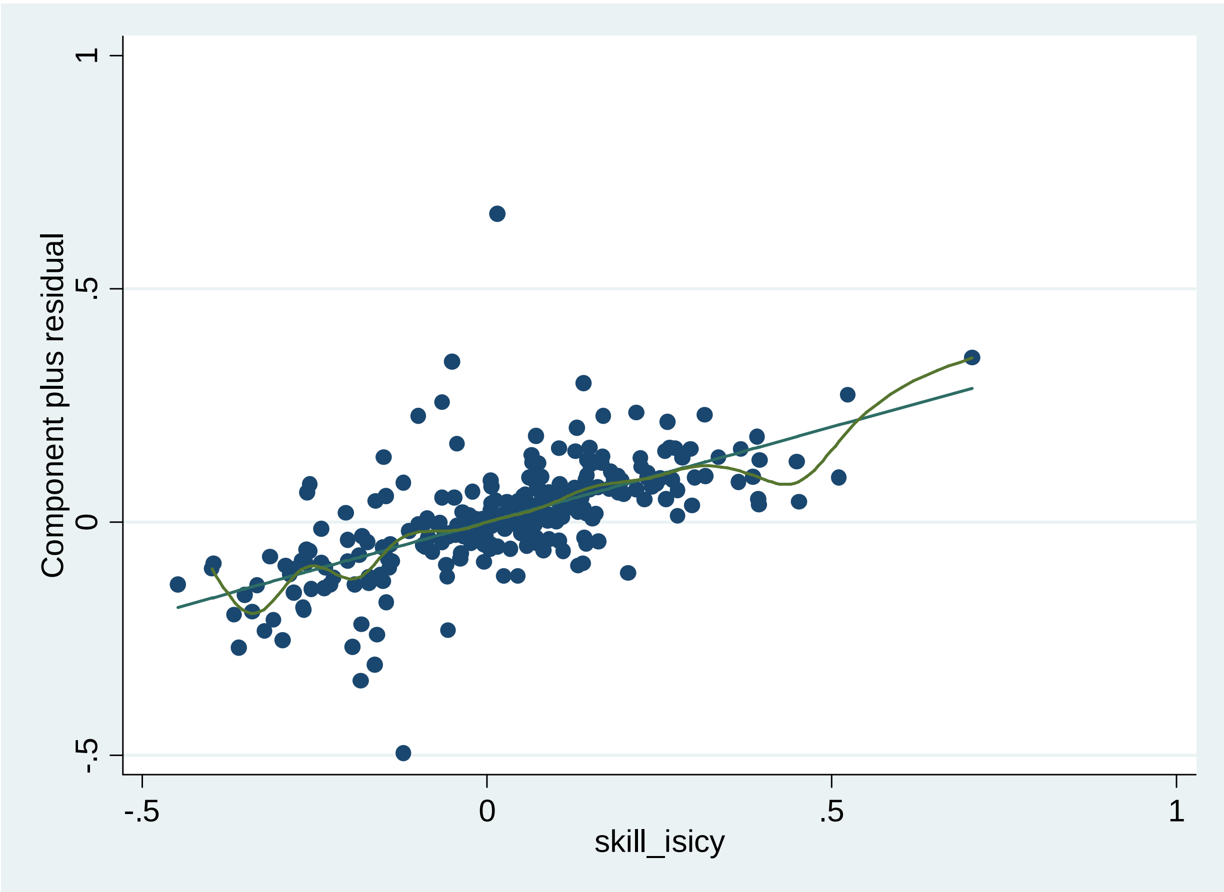
Table 6.4 - Panel regression: OLS estimator (no control for industry effects)

```
. reg  isp_inps skill_isicy, robust beta

Linear regression                                      Number of obs =     267
                                                       F(  1,   265) =   13.78
                                                       Prob > F      =  0.0003
                                                       R-squared     =  0.0401
                                                       Root MSE      =  1.6071
```

isp_inps	Coef.	Robust Std. Err.	t	P>|t|	Beta
skill_isicy	-1.776826	.4786892	-3.71	0.000	-.2002091
_cons	1.565685	.1054587	14.85	0.000	.

Figure 6.1 - Component-plus-residual plot with median spline



APPENDIX A

International Standard Industrial Classification (ISIC) – Revision 3

Code	Description
1010	Mining and agglomeration of hard coal
1020	Mining and agglomeration of lignite
1030	Extraction and agglomeration of peat
1110	Extraction of crude petroleum and natural gas
1120	Service activities incidental to oil and gas extraction excluding surveying
1200	Mining of uranium and thorium ores
1310	Mining of iron ores
1320	Mining of non-ferrous metal ores, except uranium and thorium ores
1410	Quarrying of stone, sand and clay
1421	Mining of chemical and fertilizer minerals
1422	Extraction of salt
1429	Other mining and quarrying n.e.c.
1511	Production, processing and preserving of meat and meat products
1512	Processing and preserving of fish and fish products
1513	Processing and preserving of fruit and vegetables
1514	Manufacture of vegetable and animal oils and fats
1520	Manufacture of dairy products
1531	Manufacture of grain mill products
1532	Manufacture of starches and starch products
1533	Manufacture of prepared animal feeds
1541	Manufacture of bakery products
1542	Manufacture of sugar
1543	Manufacture of cocoa, chocolate and sugar confectionery
1544	Manufacture of macaroni, noodles, couscous and similar farinaceous products
1549	Manufacture of other food products n.e.c.
1551	Distilling, rectifying and blending of spirits: ethyl alcohol production from fermented materials
1552	Manufacture of wines
1553	Manufacture of malt liquors and malt
1554	Manufacture of soft drinks production of mineral waters
1600	Manufacture of tobacco products
1711	Preparation and spinning of textile fibres; weaving of textiles
1712	Finishing of textiles
1721	Manufacture of made-up textile articles, except apparel
1722	Manufacture of carpets and rugs
1723	Manufacture of cordage, rope, twine and netting
1729	Manufacture of other textiles n.e.c.
1730	Manufacture of knitted and crocheted fabrics and articles
1810	Manufacture of wearing apparel, except fur apparel
1820	Dressing and dyeing of fur: manufacture of articles
1911	Tanning and dressing of leather
1912	Manufacture of luggage, handbags and the like, saddlery and harness
1920	Manufacture of footwear
2010	Sawmilling and planing of wood
2021	Manufacture of veneer sheets; Manufacture of plywood, laminboard, particle board and other panels and boards
2022	Manufacture of builders' carpentry and joinery
2023	Manufacture of wooden containers
2029	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials
2101	Manufacture of pulp, paper and paperboard
2102	Manufacture of corrugated paper and paperboard and of containers of paper and paperboard
2109	Manufacture of other articles of paper and paperboard
2211	Publishing of books, brochures, musical books and other publications
2212	Publishing of newspapers, journals and periodicals
2213	Publishing of recorded media
2219	Other publishing
2221	Printing
2222	Service activities related to printing

2230 Reproduction of recorded media
2310 Manufacture of coke oven products
2320 Manufacture of refined petroleum products
2330 Processing of nuclear fuel
2411 Manufacture of basic chemicals, except fertilizers and nitrogen compounds
2412 Manufacture of fertilizers and nitrogen compounds
2413 Manufacture of plastic in primary and forms and of synthetic rubber
2421 Manufacture of pesticides and other agro-chemical products
2422 Manufacture of paints, varnishes and similar coatings, printing ink and mastics
2423 Manufacture of pharmaceuticals, medicinal chemicals and botanical products
2424 Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
2429 Manufacture of other chemical products n.e.c.
2430 Manufacture of man-made fibres
2511 Manufacture of rubber tyres and tubes; retreading and rebuilding of rubber tyres
2519 Manufacture of other rubber products
2520 Manufacture of plastic products
2610 Manufacture of glass and glass products
2691 Manufacture of non-structural non-refractory ceramic ware
2692 Manufacture of refractory ceramic products
2693 Manufacture of structural non-refractory clay and ceramic products
2694 Manufacture of cement, lime and plaster
2695 Manufacture of articles of concrete, cement and plaster
2696 Cutting, shaping and finishing of stone
2699 Manufacture of other non-metallic mineral products n.e.c.
2710 Manufacture of basic iron and steel
2720 Manufacture of basic precious and non-ferrous metals
2731 Casting of iron and steel
2732 Casting of non-ferrous metals
2811 Manufacture of structural metal products
2812 Manufacture of tanks, reservoirs and containers of metal
2813 Manufacture of steam generators, except central heating hot water boilers
2891 Forging, pressing, stamping and roll-forming of metal: power metallurgy
2892 Treatment and coating of metals: general mechanical engineering on a fee or contract basis
2893 Manufacture of cutlery, hand tools and general hardware
2899 Manufacture of other fabricated metal products n.e.c.
2911 Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
2912 Manufacture of pumps, compressors, taps and valves
2913 Manufacture of bearings, gears, gearing and driving elements
2914 Manufacture of ovens, furnaces and furnace burners
2915 Manufacture of lifting and handling equipment
2919 Manufacture of other general purpose machinery
2921 Manufacture of agricultural and forestry machinery
2922 Manufacture of machine-tools
2923 Manufacture of machinery for metallurgy
2924 Manufacture of machinery for mining , quarrying and construction
2925 Manufacture of machinery for food, beverage and tobacco processing
2926 Manufacture of machinery for textile, apparel and leather production
2927 Manufacture of weapons and ammunition
2929 Manufacture of other special purpose machinery
2930 Manufacture of domestic appliances n.e.c.
3000 Manufacture of office, accounting and computing machinery
3110 Manufacture of electric motors, generators and transformers
3120 Manufacture of electricity distribution and control apparatus
3130 Manufacture of insulated wire and cable
3140 Manufacture of accumulators, primary cells and primary batteries
3150 Manufacture of electric lamps and lighting equipment
3190 Manufacture of other electrical equipment n.e.c.
3210 Manufacture of electronic valves and tubes and other electronic components
3220 Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy
3230 Manufacture of television and radio receivers, sound or video recording or reproducing apparatus, and associated goods
3311 Manufacture of medical and surgical equipment and orthopaedic appliances

3312 Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment
3313 Manufacture of industrial process control equipment
3320 Manufacture of optical instruments and photographic equipment
3330 Manufacture of watches and clocks
3410 Manufacture of motor vehicles
3420 Manufacture of bodies (coachwork) for motor vehicles: manufacture of trailers and semi-trailers
3430 Manufacture of parts and accessories for motor vehicles and their engines
3511 Building and repairing of ships
3512 Building and repairing of pleasure and sporting boats
3520 Manufacture of railway and tramway locomotives and rolling stock
3530 Manufacture of aircraft and spacecraft
3591 Manufacture of motorcycles
3592 Manufacture of bicycles and invalid carriages
3599 Manufacture of other transport equipment n.e.c.
3610 Manufacture of furniture
3691 Manufacture of jewellery and related articles
3692 Manufacture of musical instruments
3693 Manufacture of sports goods
3694 Manufacture of games and toys
3699 Other manufacturing n.e.c.
3710 Recycling of metal waste and scrap
3720 Recycling of non-metal waste and scrap