Skill Bias in Italy: a Gauss-Newton non Linear Regression Analysis

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Abstract

The aim of this work is to propose a new methodology to evaluate the characteristics of the technological change and the contribution of skilled and unskilled labour shares in explaining productivity changes. We apply this methodology to study the technological change occurred in Italy evaluating if in the Italian manufacturing sector the technological change has been skill biased during the late 90's. Previous studies do not report clear evidence of the phenomenon known as Skill Biased Technological Change. In our work the methodology used consists in estimating a CES production function using a non linear method. We estimate the productivity due to technologies that are not Hicks neutral and we evaluate if firms that have increased the number of skilled workers perform *ceteris paribus* a greater productivity. Our results seem to confirm that the firms' productivity level increases independently on the larger employment of skilled or unskilled workers.

Theme: Skill Biased Technological Change

Jel classification: O30, O33.

Key Words: Skill Biased Technological Change, Gauss-Newton non Linear Regression.

1 Introduction

In this work we propose a new methodology to evaluate the characteristics of the technological change and the contribution of skilled and unskilled labour shares in explaining productivity changes. We apply this methodology to study the technological change occurred in Italy during the late '90s.[1] This study is motivated by the lack of a clear evidence concerning the complementarity between new technologies and the skilled labour force in the Italian economy. For instance, an analysis implemented by Piva and Vivarelli (2001) based an a large sample of Italian Manufacturing firms does not report clear evidence on the phenomenon known as Skill Biased Technological Change (SBTC). In our work the methodology used consists in estimating a CES production function, using a non linear method, for 4017 manufacturing firms in the period 1998-2000. We estimate the productivity due to technologies that are not Hicks neutral and, by replicating the methodology used in Khan and Lim (1998), we evaluate if firms that have increased the number of skilled workers perform *ceteris paribus* a greater productivity. Our results seem to confirm that in the period 1998-2000 the firms' productivity level increases independently on the share of skilled or unskilled workers. No SBTC seems to be occurred in the Italian manufacturing sector in this period.

2 Gauss-Newton non Linear- Regression Model

In this section we describe and motivate the econometric methodologies used to estimate the firms' productivity change due to no-Hicks neutral technological change and to establish the link between the change in productivity and the labour force composition.

Consider the following implicit production function with an Hicks neutral technology T_{it}:

$$Y_i = T_{it} f(K_{it}, UL_{it}, SL_{it}) \tag{1}$$

where Y_{it} indicates the production level of the i firm at time t, K_{it} indicates the capital stock and UL_{it} and SL_{it} indicate the unskilled and the skilled labour respectively. The simplest strategy to estimate the technology's contribution to the production level in each firm consists in taking logarithms of both sides in equation (1), taking derivatives with respect to time and estimating the TFP growth rate or Solow residual (g) as indicated in equation (2) where, a dot above a variable indicates its derivative with respect to time and F_j, with $j = K, SL, UL$, indicates the marginal productivity of factor j and the subscripts i and t are omitted for notational simplicity. Imposing a Cobb-Douglas production function with a multiplicative random error $\varepsilon_{it} \sim \mathcal{N}(0, \sigma^2)$, where $\mathcal{N}$ indicates a normal distribution, allows us to estimate the TFP growth in each firm by using the OLS method:

$$g = \dot{Y}/Y - (\frac{F_K K}{Y}) * (\dot{K}/K) - (\frac{F_{UL} UL}{Y}) * (\dot{UL}/UL) - (\frac{F_{SL} SL}{Y}) * (\dot{SL}/SL) \quad (2)$$

Unfortunately, this approach is not useful for our aim for at least two reasons. First, the estimates of a Cobb Douglas production function are based on the hypothesis of constant factors' elasticity of substitution equal to one. This assumption reflects constant returns to scale which are required to estimate TFP growth rate by using the factors price as a proxy for the factors productivity. A factors' elasticity of substitution equal to one does not allow for any bias in the technological change. Estimating a Cobb-Douglas implies the assumption of no possible bias in the technological change.

Second, even if we use the methodology indicated in Morrison (1992) to consider increasing returns to scale, a great part of the TFP estimates obtained by using OLS would be, by definition, orthogonal to the regressors:[2]

$$E[\widehat{\varepsilon}_i | \log K_i, \log UL_i, \log SL_i] = 0 \quad (3)$$

As a consequence we could not analyze the relationship between the productivity change and the changes in the labour force composition.

To overcome these problems we assume that the production function is a CES expressed as follows:

$$Y_i = A[\alpha_k K_i^{-\rho} + \alpha_u UL_i^{-\rho} + \alpha_s SL_i^{-\rho}]^{-\phi/\rho} \quad (4)$$

where α_j is the relative share of factor j with $\sum_j \alpha_j = 1 \ for \ j = k, u, s.$

This production function is typically not linearizable unless we do not use a Taylor approximation in $\rho = 0$. But this approximation would lead us, once again, to the Cobb-Douglas case with factors elasticity of substitution equal to one.

We estimate this production function by using the Gauss-Newton non linear regression model (GNR).

Consider a sample of two random variables z_n and x_n i.i.d. with $n = 1, 2, ...N$. Assume that:

$$z_n|x_n \backsim \mathcal{N}(\mu(\beta_0, x_n); \sigma_0^2) \tag{5}$$

where $\mu : \mathbb{R}^k * \mathbb{R}^k \to \mathbb{R}$ is a continuous function two time differentiable in β.

In the following non linear regression model:

$$z_n = \mu(\beta_0, x_n) + \varepsilon_n \tag{6}$$

estimated using the GNR, the following results hold:

$$E[\widehat{\varepsilon}_n|\mu(\beta_0, x_n)] = 0 \tag{7}$$

$$E[\widehat{\varepsilon}_n|\nu(\lambda_0, x_n)] \neq 0 \tag{8}$$

for $\nu(\cdot) \neq \mu(\cdot)$. These imply that the regressors in (6), and their non linear transformations different from $\mu(\cdot)$, are not orthogonal to the residuals ε_n. In other words, we can estimate the relationship that links the changes in the production factors with the changes in productivity generated by the technological change.

3 Data Description and Variables Construction

The data we use come from the survey "Indagine sulle Imprese Manifatturiere" by Mediocredito Centrale. The survey contains 4017 manufacturing firms. Data are available from 1998 to 2000. This survey contains standard balance sheet data for each firm and many informations concerning the labour force and it allows us to discriminate between skilled and unskilled worker in each firm. According to Khan and Lim (1998), Machin and van Reenen (1998) and Berman *et al.* (1998) the separation between skilled and unskilled workers is made by distinguishing between workers that are not involved directly in the product realization' process and workers that participate directly to the physical product realization. A measure of the firms' cost for skilled and unskilled labour is obtained by weighting the cost of labour indicated in the balance sheet by the number of skilled and unskilled workers and by the "labour cost per hour" for skilled and unskilled worker published by the National Statistical Bureau (ISTAT). According to previous studies, the Value Added is used as a measure for production. It is worth noting that the main results are completely not affected by this choice and they hold entirely if we use the value of sales as a proxy for production. We use the sum of materials and the capital depreciation as indicated in the balance sheets as a measure for the capital stock. Also in this case, the results do not change if we use different measures of capital.

4 The Empirical Analysis

The empirical analysis consists in the estimation of the CES cost function expressed in equation (4). The estimation is implemented by using the non linear least squares by using the Gauss-Newton procedure.

The residuals are given by

$$\widehat{\varepsilon}_i = Y_i - \widehat{A}[\widehat{\alpha}_k K_i^{-\widehat{\rho}} + \widehat{\alpha}_u UL_i^{-\widehat{\rho}} + \widehat{\alpha}_s SL_i^{-\widehat{\rho}}]^{-\widehat{\phi}/\widehat{\rho}} \tag{9}$$

In this measure of unexplained productivity the hicksian neutral technologies are excluded. It is important to note that we do not impose constant return to scale by imposing $\phi = 1$. We leave this parameter to be determined by the sample.

Once the residuals have been estimated, it is possible to check if this measure of unexplained productivity increased in firms that have employed more skilled workers.

The following non linear equation is estimated:

$$Y_i = \beta_o(\frac{\beta_1}{\beta_1+\beta_2+\beta_3}K_i^{-\beta_4} + \frac{\beta_2}{\beta_1+\beta_2+\beta_3}UL_i^{-\beta_4} + \frac{\beta_3}{\beta_1+\beta_2+\beta_3}SL_i^{-\beta_4})^{-\beta_5/\beta_4} + \varepsilon_i \tag{10}$$

The parameters of this model are estimated by the GNR. Consider the two random variables z_n and x_n defined as indicated in section 2.

For simplicity, indicate $\mu(\beta)= \mu(\beta_0, x_n)$ and $\omega(\beta) = \frac{\partial \mu(\beta)}{\partial \beta}$

The search direction for the parameters that maximize the Maximum Likelihood function is given by.

$$\delta_{GNR}(\beta) = [\omega(\beta)'\omega(\beta)]^{-1}\omega(\beta)'[z_n - \mu(\beta)] \tag{11}$$

This means that the search direction is given by the coefficients of an hypothetical linear regression of the residuals, $z_n - \mu(\beta)$, on the partial derivative of the non linear function, $\omega(\beta)$.

Given the step size $\lambda = 1$ the GNR proceeds by using the scoring method: the parameter is estimated when convergence is achieved in the following expression:

$$\beta_{i+1} = \beta_i + [\omega(\beta)'\omega(\beta)]^{-1}\omega(\beta)'[z_n - \mu(\beta)] \tag{12}$$

According to Green (2003) and Ruud (2000), the initial values imposed to start the iteration process are the OLS estimates of the linear regression contained in equation (**??**):

$$\log Y_i = \log A + \alpha \log K_i + \gamma \log UL_i + \delta \log SL_i \tag{13}$$

The initial values of the parameters $\beta_{1,}$ β_2 and β_3 in (10) are not identified starting from α γ δ unless we impose some restrictions. Imposing different restrictions generates changes in the absolute value of each parameter, but their ratios remain unchanged. The estimates of the CES production function for years 2000, 1999, 1998 are reported in Table 1 Table 2 and Table 3 respectively. The results are very similar to the ones obtained by Bodkin and Klein (1967) who estimate a CES production function as indicated in equation (4) for a sample of manufacturing firms in the US.

In this stage, the most important statistical tests need to be carried out on the parameters β_4 and β_5 which represent the elasticity of substitution and the returns to scale respectively. The t test on β_4 rejects the hypothesis that β_4 is equal to zero in all the regressions. This result implies that the hypothesis that the manufacturing sector production function is represented by a Cobb-Douglas with factors elasticity of substitution equal to one may be rejected. Moreover a skilled labour augmenting technological progress implies a skill biased technological change only if the elasticity of substitution is greater than one (Khan and Lim, 1998). Hence, we can check for the presence of a skilled labour augmenting technological progress as a signal for SBTC.

The t-test on the parameter β_5 confirms the presence of increasing returns to scale for the years 1999 and 2000.

Now, we can implement the second stage of the econometric strategy: we want to establish if unexplained productivity, that is:

$$\widehat{\varepsilon}_i = Y_i - \widehat{\beta}_o\left(\frac{\widehat{\beta}_1}{\widehat{\beta}_1 + \widehat{\beta}_2 + \widehat{\beta}_3} K_i^{-\widehat{\beta}_4} + \frac{\widehat{\beta}_2}{\widehat{\beta}_1 + \widehat{\beta}_2 + \widehat{\beta}_3} UL_i^{-\widehat{\beta}_4} + \frac{\widehat{\beta}_3}{\widehat{\beta}_1 + \widehat{\beta}_2 + \widehat{\beta}_3} SL_i^{-\widehat{\beta}_4}\right)^{-\widehat{\beta}_5/\widehat{\beta}_4} \tag{14}$$

increased in firms that increased skilled relative to the unskilled workers.
Hence, we implement the following regression:

$$\log(\widehat{\varepsilon}_{i,00} - \widehat{\varepsilon}_{i,98}) = a + b\log(K_{i,00} - K_{i,98}) + c\log(skilled_{i,00} - skilled_{i,98}) + ... \\ ... + d\log(uskilled_{i,00} - uskilled_{i,98}) + u_i \quad (15)$$

where the variables *skilled* and *uskilled* indicate the number of skilled and unskilled workers respectively. We use this time range to generate differences referred to the largest available period. However, for period 1998-1999 and 1999-2000 the results discussed below hold entirely. Table 1.4 contains the estimated parameters. All the variables have coefficients significantly different from zero.

The most important result concerns the parameters associated to the variables $\log(skilled_{i,00} - skilled_{i,98})$ and $\log(uskilled_{i,00} - uskilled_{i,98})$. As indicated in Table 4, we cannot reject the hypothesis that the two parameters are equal to each other. The increases in the unexplained productivity in each firm is due to the increases of skilled labour and to the increases of unskilled labour in the same measure.

This evidence confirms the result obtained in previous studies aimed to investigate the presence of SBTC in the Italian manufacturing firms.

The productivity rise in each firm seems to be due to the increase of skilled labour as well as to the increase of unskilled labour in the same measure. Any innovation occurred in the period 1998-2000 seems to have been both skilled and unskilled labour augmenting. There is no evidence of a clear skill bias in the technological change that characterizes the Italian manufacturing sector.

5 Conclusions

In this work we propose a new methodology to evaluate the characteristics of the technological change and the contribution of skilled and unskilled labour shares in explaining productivity changes. We apply this methodology to study the technological change occurred in Italy during the '90s. By using a sample of 4017 firms we investigate the presence of a skill biased technological change by looking directly at the firm's productivity. By using a Gauss-Newton non linear regression we estimate the firms' productivity changes generated by no Hicks' neutral technological change and we test if changes in productivity are greater in firms that decided to employ relatively more skilled workers. We do not find any evidence that in this period firms that employed more skilled workers performed an higher productivity than firms that increased the number of unskilled workers. This result seems to confirm the results of previous studies aimed at establishing if the Italian manufacturing sector presents peculiarities with respect to other developed countries. This work highlights that the SBTC seems to be a phenomenon that did not affect the Italian manufacturing sector in the late '90s. Further research targeted to establish the (possibly institutional) factors that prevent this bias in the technological change, making Italy a particular case among developed countries, needs to be carried out.

Notes

1. The Skill Biased Technological Change has been investigated in many studies. Among all see Autor *et al.* (1998), Berman *et al.* (1994), Berman *et al.* (1998), Bound and Johnson (1992), Kahn and Lim (1998), Machin and van Reenen (1998), Katz and Murphy (1992) and Wood (1994).

2. The symbol ^ on a parameter indicates that we are referring to its estimated value.

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Table 1-CES Estimates using GNR- 2000

Dep. Var: Y_i				N° Obs. 4017 Adg. R-sq: 0.9481
	Coef.	t	*Std.Err.*	
$\widehat{\beta}_0$	1.0855	18.78	0.0578	
$\widehat{\beta}_1$	0.0045144	30.14	0.0001498	
$\widehat{\beta}_2$	0.01	-	-	
$\widehat{\beta}_3$	0.0026657	12.34	0.000216	
$\widehat{\beta}_4$	-0.1866	-6.72	0.0277955	
$\widehat{\beta}_5$	1.100204	251.31	0.0043779	

The standard deviations are asymptotic approximations

Table 2-CES Estimates using GNR-1999

Dep.Var: Y_i				N° Obs. 4017 Adg. R-sq: 0.9427
	Coef.	t	*Std.Err.*	
$\widehat{\beta}_0$	3.3134	20.28	0.1634148	
$\widehat{\beta}_1$	0.003769	26.12	0.0001443	
$\widehat{\beta}_2$	0.01	-	-	
$\widehat{\beta}_3$	0.008984	12.36	0.0007268	
$\widehat{\beta}_4$	-0.80182	-18.25	0.0439315	
$\widehat{\beta}_5$	1.0053	252.71	0.0039781	

The standard deviations are asymptotic approximations

Table 3-CES Estimates using GNR-1998

Dep. Var: Y_i				N° Obs. 4015 Adg. R-sq: 0.9394
	Coef.	t	*Std.Err.*	
$\widehat{\beta}_0$	4.3265	19.77	0.2188	
$\widehat{\beta}_1$	0.0083119	27.12	0.0003	
$\widehat{\beta}_2$	0.0212	-	-	
$\widehat{\beta}_3$	0.01628	10.44	0.00156	
$\widehat{\beta}_4$	-0.77501	-17.26	0.044909	
$\widehat{\beta}_5$	0.9718474	250.65	0.003877	

The standard deviations are asymptotic approximations

Table 4-Estimates of the CES residuals regressed on Production Factors

Dep. Variable: $\log(\widehat{\varepsilon}_{i,00} - \widehat{\varepsilon}_{i,98})$				N° Obs. 732 Adg. R-sq: 0.3503
	Coef.	*t*	*Std.Err*	
$\widehat{a}$	5.9843	19.91	0.3005	
$\widehat{b}$	0.1025	1.82	0.0564	
$\widehat{c}$	0.3748	3.62	0.1036	
$\widehat{d}$	0.1623	2.32	0.0700	

Test F: H_0: $\widehat{c} - \widehat{d} = 0$

F(1,116)=2.16 ⇒Prob>F=0.1441