Laboratory of Economics and Management
Sant'Anna School of Advanced Studies

Piazza Martiri della Libertà, 33 - 56127 PISA (Italy)
Tel. +39-050-883-343 Fax +39-050-883-344
Email: lem@sssup.it Web Page: http://www.lem.sssup.it/

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Characterizing the Production Process: A Disaggregated Analysis of Italian Manufacturing Firms

Giulio Bottazzi*
Marco Grazzi*
Angelo Secchi*

*Laboratory of Economics and Management,
Sant'Anna School for Advanced Studies

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Characterizing the Production Process: A Disaggregated Analysis of Italian Manufacturing Firms*

Giulio Bottazzi Marco Grazzi [†] Angelo Secchi

Scuola Superiore Sant'Anna, Pisa

Abstract

This paper provides a description of the production process by comparing different frameworks in which to analyze the relations between inputs and output. The analyses are performed on a representative sample of Italian manufacturing firms. We employ both parametric and non-parametric analysis. The latter allows to detect the presence of heterogeneity in the way the production is carried out within each sector.

Results of the econometric analysis show that coefficient estimates tend to be robust with respect to the different models employed.

JEL codes: C1, L2, L6
Keyword: Input Output Relation, Panel Data, Returns to Scale, Labor Productivity.

Sintesi

Questo articolo propone una descrizione del processo produttivo che permette di confrontare differenti approcci presenti in letteratura. L'analisi presentata fa riferimento ad un campione rappresentativo delle imprese italiane nel settore manifatturiero. Si impiegano sia metodi parametrici che nonparametrici. Questi ultimi permettono di individuare un elevato grado di eterogeneità nel modo in cui è effettuata la produzione da imprese in uno stesso settore.

I risultati dell'analisi econometrica evidenziano come i coefficienti stimati siano poco sensibili alla scelta del modello.

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† *Corresponding Author*: Marco Grazzi, *E-mail*: grazzi@sssup.it.

1 Introduction

Describing the production technology has traditionally proved to be a relevant and appealing issue in economics. Such a characterization allows indeed to address a number of meaningful questions as the extent of substitutability or complementarity of inputs, the source of productivity differences across firms (and its measurement) or the magnitude of economies of scale, to mention but a few.

An important strand of research[1] in this field has tried to characterize the production process of firms by means of production functions with relatively simple functional forms. The early representation of Cobb and Douglas [1928] is still widely adopted due to its nice properties. Different kinds of investigations were performed on the Cobb-Douglas production function and also on other specifications intended to relax some of the assumptions underlying this traditional model. Early works had been largely cross-sectional but as time-series data became available it was a natural development to take into explicit account the role of time (cfr. the historical note in Griliches [1996]). Even if the need to choose the individual firm as the level of investigation was immediately recognized,[2] a common limitation of these early works was their focus on an aggregate production function, mostly due to the unavailability of more disaggregated data.

Recently the availability of longitudinal micro-level data sets (LMD) has largely increased the interest in describing the production activities of business firms and, in particular, in measuring their productivity and dynamics (see Baily et al. [1992] and the review in Bartelsman and Doms [2000]). At the same time, the desire to disentangle the empirical description of the production process from a strict set of assumptions about the technology choices available to firms and their preferences led to the development of a large literature which, applying non-parametric techniques, is interested in describing the production activities of the different firms composing a sector or an industry, ultimately identifying the so-called *efficient frontier* of the production. This approach is purported to reconstruct a benchmark of the industry, so that each firm can be compared with the best performer for each level of scale of the activity (see for instance Varian [1984]).

In this paper we propose a "disaggregated" analysis aimed at exploring how the production process is carried out in different manufacturing sectors. We apply non-parametric techniques without following the "efficient frontier" tradition since we do not want to define any sort of "optimal" mixtures of inputs for the firms operating in a given sector. Rather, we use a descriptive approach trying to obtain a succinct description of the production activity in each sector and to provide an account of how the mix of inputs varies across industries and in time. This enables us also to keep track of how relative input intensities vary, in a given sector, with the size of the firm. Furthermore we consider a parametric approach, adopting a standard form for the sectoral production function, and we present estimations of the inputs-output relationship, based on different methods designed to exploit the longitudinal structure of our database. With this respect, the main finding is that the estimated technical coefficients seem not very sensitive to the choice of method.

The paper is organized as follows. In Section 2 we briefly describe the nature and structure of our data. In Section 3 a first exploratory investigation, based on non-parametric method is

[1] In this paper we neglect at least one another important line of research: the one developed out of the national income measurement tradition, based largely on the work of NBER under the leadership of Simon Kuznets.

[2] For instance, Marschak and Andrews [1944] say that *"it is the firm, not the country, state or industry, that chooses the resources and (more or less) tries to maximize the profit"* (p. 169).

presented. The parametric part of our analysis is described in Section 4 while in Section 5 we summarize our conclusions.

2 Data

The research we present here draws upon the MICRO.1 databank developed by the Italian Statistical Office (ISTAT)[3]. MICRO.1 contains longitudinal data on a panel of several thousands of Italian manufacturing firms with employment of 20 units or more and it covers the years 1989-97. As reported in Bartelsman et al. [2004] the percentage of manufacturing firms with more than 20 employees is the 12% of the total population. However, these relative larger companies account for almost 70% in terms of employment in the manufacturing sector.

Firms are classified according to their sector of principal activity following the ISIC classification. The database contains information on many variables appearing in a firms balance sheet. The "panel" nature of the database allows us to keep track of the same firm during the considered interval. The richness of the cross-sectional dimension of the sample allows to partially overcome shortcomings due to the limited time span of the dataset. In this work we have chosen total sales plus (or minus) the variation of unsold stocks as a proxy for output. Labor is proxied by number of employees and capital by tangible fixed assets; and in particular by the amount that corresponds to the original historic cost.

3 Non Parametric Analysis

We begin our analysis with a non parametric investigation of the relation between the two factors of production considered, capital and labor, and firms output.

A first question concerns the degree of heterogeneity in the amount of inputs used in a given sector. Let $l_i = \log(L_i)$ and $k_i = \log(K_i)$ where $i \in \{1, \ldots, N\}$ be respectively the number of employees and the capital of firm i in a sector with N firms. We can represent the fraction $f(l, k)$ of firms using a given amount of inputs (l, k) using a kernel density estimate obtained from observed data

$$\hat{f}(l, k) = \frac{1}{N\, h_l\, h_k} \sum_{i=1}^{N} K\left(\frac{l - l_i}{h_l}, \frac{k - k_i}{h_k}\right) \tag{1}$$

where h_l and h_k are bandwidth parameters controlling the degree of smoothness of the density estimate and where K is a kernel density, i.e. $K(x, y) \geq 0, \forall x, y \in (-\infty, +\infty)$ and $\int dxdyK(x) = 1$. The kernel density estimate can be considered a smoothed version of the histogram obtained counting the observations in different bins. It relies on the provision of two objects: the kernel[4] K and the bandwidths h_l and h_k.

The results for four different sectors are reported in Fig. 1 (left side plots) for the year 1997. For any couple of input quantities (l, k), the height of the surface is proportional to the probability of finding a firm using that amount of inputs. The distributions appear to have a rather wide support which spans several orders of magnitude in both capital and number of employees. This confirms the well known fact that firms of very different sizes coexist inside

[3]The database has been made available to our team under the mandatory condition of censorship of any individual information.

[4]Throughout this paper the kernel function will always be the Silverman Type II density defined in Silverman [1986].

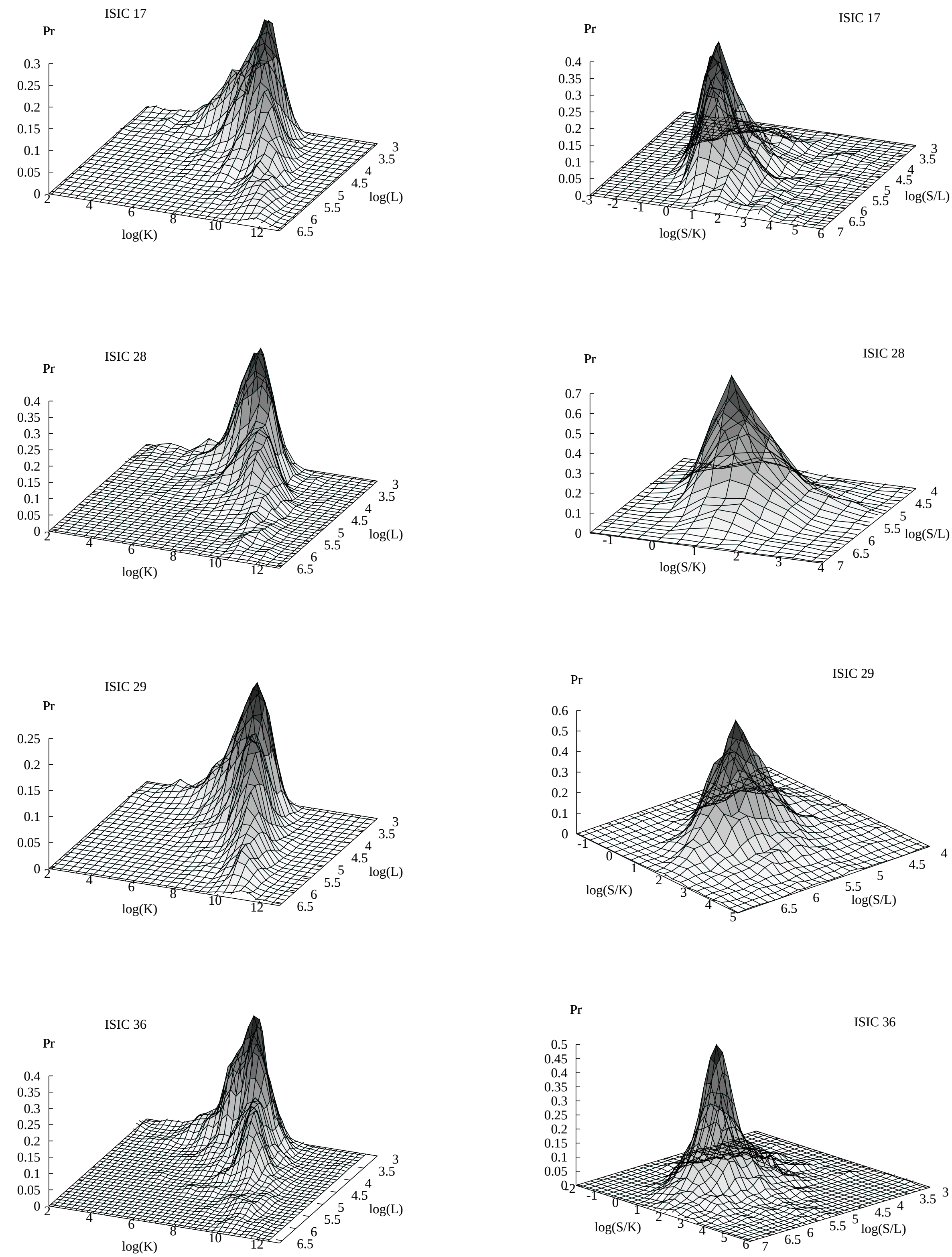

Figure 1: **(Left Side)** Kernel density estimate of (k, l) in 1997 for 4 different manufacturing sectors. **(Right Side)** Kernel density estimate of $(\log(S/K), \log(S/L))$ in the same year and for the same sectors.

SECTOR	ISIC	$\log(S/K)$		$\log(S/L)$		$\rho(\Delta_\tau k, \Delta_\tau l)$					
						$\tau = 1$		$\tau = 5$		$\tau = 9$	
	Code	Mean	Std Dev.	Mean	Std Dev.	Coeff.	Std Err.	Coeff.	Std Err.	Coeff.	Std Err.
Food/Beverages	15	1.18	1.15	6.06	0.81	0.125	0.011	0.279	0.018	0.345	0.042
Textiles	17	0.89	1.14	5.28	0.73	0.136	0.009	0.326	0.015	0.376	0.037
Leather/Footwear	19	1.94	1.13	5.14	0.90	0.080	0.013	0.203	0.023	0.292	0.065
Wood Manufact.	20	1.04	1.04	5.35	0.65	0.111	0.017	0.242	0.029	0.379	0.069
Paper/Allied Prod.	21	0.86	1.11	5.68	0.59	0.111	0.018	0.275	0.029	0.302	0.067
Chemicals Prod.	24	1.16	1.14	6.04	0.64	0.183	0.014	0.409	0.023	0.441	0.052
Rubber/Plastics	25	1.06	0.96	5.52	0.60	0.133	0.012	0.297	0.021	0.339	0.046
Basic Metals	27	1.00	1.06	5.80	0.73	0.125	0.016	0.199	0.025	0.247	0.057
Metal Products	28	1.09	1.12	5.25	0.58	0.094	0.008	0.248	0.014	0.289	0.033
Indust. Machinery	29	1.50	1.06	5.51	0.54	0.105	0.008	0.273	0.013	0.391	0.029
Electr. Machinery	31	1.56	1.08	5.41	0.63	0.128	0.013	0.318	0.024	0.339	0.055
Furniture Manuf.	36	1.39	1.07	5.33	0.62	0.106	0.010	0.247	0.017	0.270	0.040

Table 1: Descriptive statistics of $\log(S/K)$ and $\log(S/L)$ in 1997. Cross correlation coefficient $\rho(\Delta_\tau k, \Delta_\tau l)$ for different time horizons τ with standard error expressed as the inverse square root of the number of observations.

the same manufacturing sector. We have checked that the width of the distribution and its shape is essentially invariant across the years covered by our databases, for all the sectors under investigation. Not only the sizes of the firms are different, but also the intensity with which the different inputs contribute to firm output can be shown to vary to a large extent. In the right side plots of Fig. 1 we report, for the same sectors, the two dimensional density of the logarithms of input intensities $\log(S/K)$ and $log(S/L)$ estimated using (1). As can be seen, the support of the distributions is again quite wide: firms belonging to the same sector seem to possess very different production structures. For instance in the Textiles sector (ISIC 17) firms with a value of $\log(S/K)$ around 1 coexist with firms with a value larger than 2. This implies a more than twofold difference in the capital productivity. The same can be said for the number of employees: in line with previous investigation reported in Bottazzi et al. [2002] we observe the coexistence in the same sector of firms with very different labour productivity $\log(S/L)$. In the Textiles sector (ISIC 17) this quantity spans values from 4 to 6, corresponding to a labor productivity ranging from around 50 to around 400 million Lire[5] per employee. Even if the distribution of capital and labor productivities is broad in all sectors, the sectoral specificities clearly emerge in their averages: the average value of $\log(S/K)$ ranges from 0.86 in the Paper and Allied Products sector (ISIC 21) to 1.94 in the Leather and Footwear sector (ISIC 19) while the labor productivity ranges from 5.14 (around 170 million 1997 Lire per employee) in the Leather and Footwear sector (ISIC 19) to 6.06 (around 428 million 1997 Lire per employee) in the Food and Beverages sector (ISIC 15). Table 1 reports mean and standard deviation of $\log(S/K)$ and $\log(S/K)$ for all the sectors analyzed.

Next we move to the description of how the two inputs under analysis enters in the production process of the different firms operating in a given sector. In other terms, we want to analyse how, inside a given sector, the response variable, output, depends on a vector of input variables, namely capital and labor. The clear heterogeneous nature of the firms operating in the same sector suggests that the analysis of the input-output relation cannot be performed simply looking at the average intensities or, in general, at some aggregate quantities. A clear representation of the sectoral structure of the production activity can be obtained using a multivariate kernel regression. This is a non-parametric description which does not impose any *a priori* structure on the data themselves [Pagan and Ullah, 1999, Härdle et al., 2004]. We are interested in estimating the conditional expectation of output $E(s|(k,l))$ given a certain

[5] 1997 nominal value.

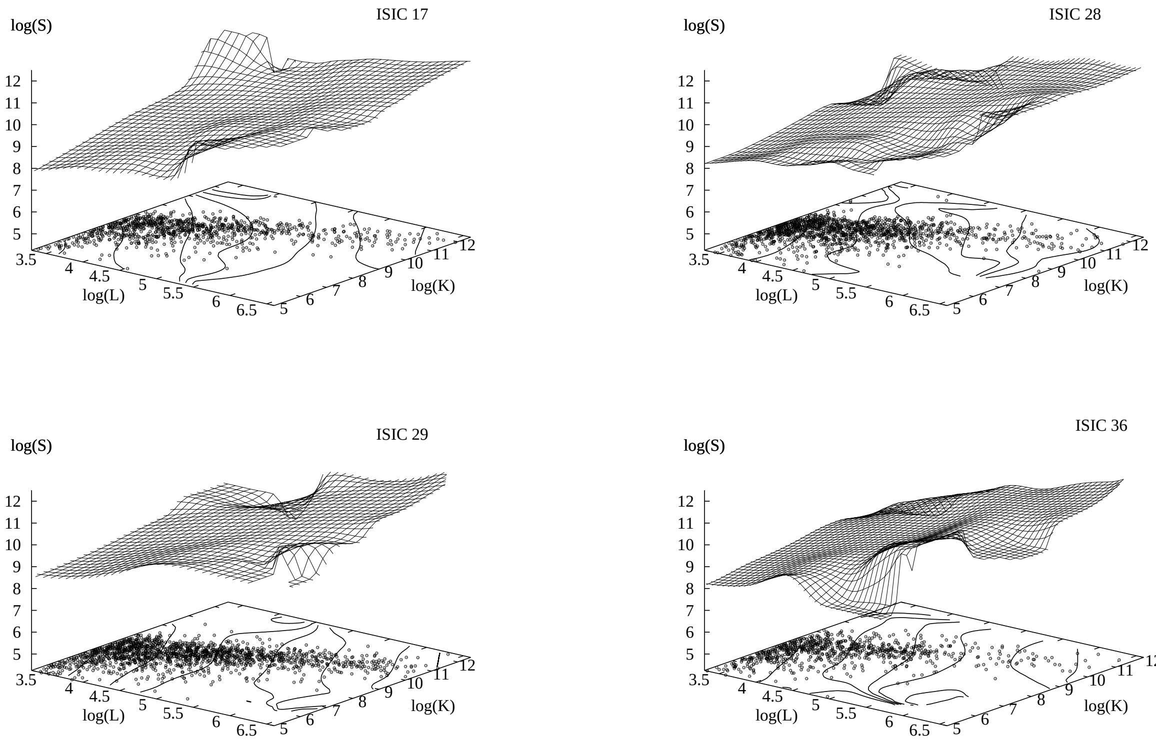

Figure 2: Kernel estimate of the conditional expectation of output $\hat{E}(s|(k,l))$ in 1997 in 4 different sectors. The estimation is computed in 60 points.

amount of inputs (k,l)

$$E[s|(k,l)] = \int s\, f(s|k,l)\, ds = \frac{\int s\, f(s,k,l) ds}{f(k,l)} \tag{2}$$

where $f(s,k,l)$ is the joint probability density of having output level s, capital k and an employment level (in log) equal to l. Replacing $f(s,k,l)$ with the multivariate kernel density estimates $\hat{f}(s,k,l)$ defined in analogy with (1) a kernel estimation of the expected output $\hat{E}(s|(k,l))$ can be defined [Silverman, 1986]

$$\hat{E}[s|(k,l)] = \frac{\displaystyle\sum_{i=1}^{N} s_i\, K\left(\frac{k-k_i}{h_k}, \frac{l-l_i}{h_l}\right)}{\displaystyle\sum_{i=1}^{N} K\left(\frac{k-k_i}{h_k}, \frac{l-l_i}{h_l}\right)} \tag{3}$$

using the observed levels of output and input utilization (s_i, k_i, l_i) of the N firms operating in a sector. The resulting conditional expectation functions $\hat{E}(s|(k,l))$ for four sectors are shown in Fig 2. To each combination of (log) capital k and (log) labor l, on x and y axis corresponds the relative level of output s, on the z axis. Using the kernel estimation technique, smooth surfaces have been obtained from the discrete sets of observations. As a reference, the location of the observed amount of inputs (k,l) has been reported on the basis of plots. The use logarithmic scales allows us to represent firms of very different dimensions on the same plot so

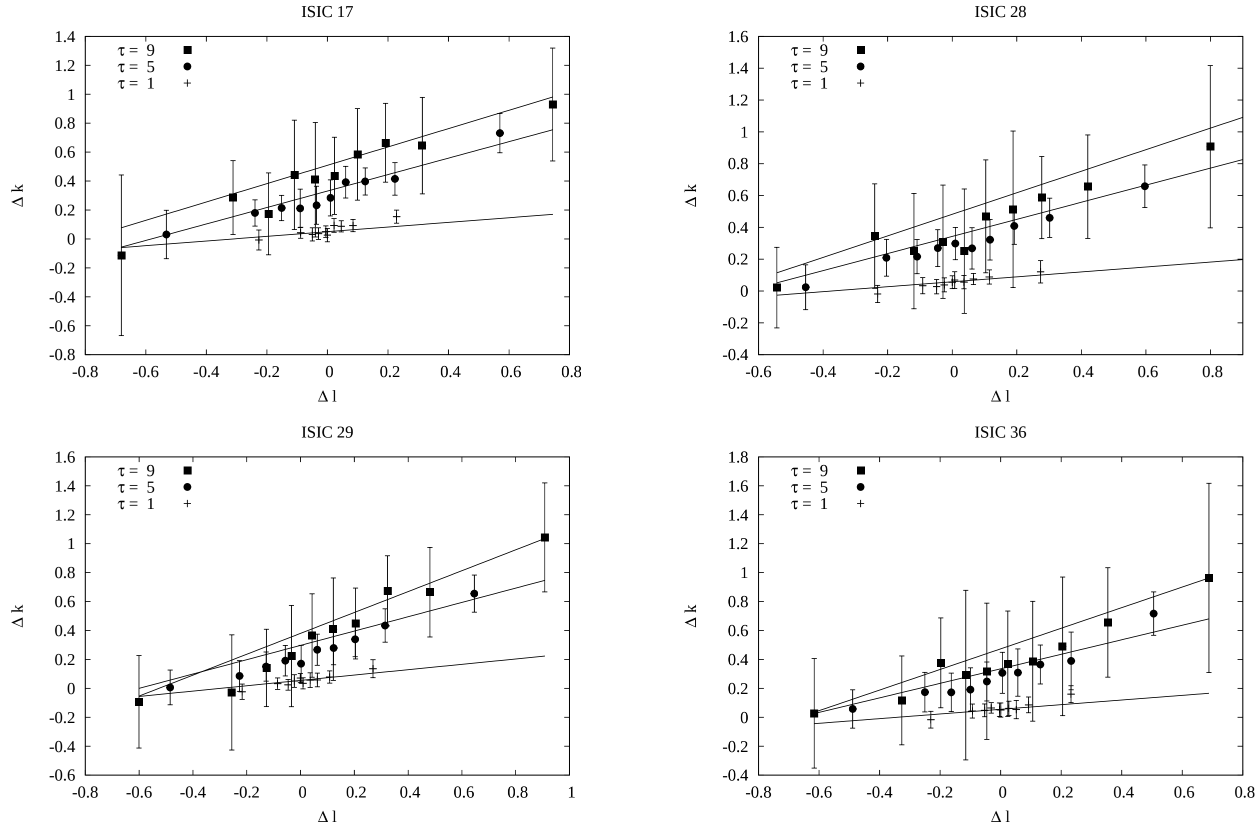

Figure 3: Binned scatter plots of Δk versus Δl for different time horizons τ in 4 different sectors. A robust linear fit which minimize the mean absolute deviation is also reported.

that the identification of possible patterns becomes possible. Some features of Fig. 2 are more explicit, whereas others deserve more accurate comments. First of all, as expected, output is an increasing function of both factors and this function seems to be well described, at least globally, by a plane in the (s, k, l) space. These plots confirm the heterogeneity in technologies within a single sector revealed by the analysis of the empirical probability densities reported in Fig 1 and show how a given level of output is attainable with significantly different mix of inputs. This is particularly true for smaller firms where a certain "tolerance" to possible inefficiencies in input usage seems to be present. Indeed, looking at the disperse distributions of couples (k, l) for the different firms inside a sector (small black dots on the plot basis of Fig. 2) we observe that very different levels of inputs can be associated with the same level of output. Surely these differences in the strength and pace of competition are worth of further exploration (Winter [2002]). Moreover, our analysis reveals that the observed heterogeneity in inputs utilization is persistent over time and we do not find any evidence of convergence towards a common mixture, for instance in the form of some reduction in the variance of the sectoral distribution of capital S/K or of labor S/L productivity.

Notwithstanding the permanent character of the width of the input distributions, both in their level, l and k, and in their respective productivities, it is interesting to analyze the structure of their evolution across time. In particular, we are interested in the relation among the firms growth rate when its size is measured in terms of different inputs[6]. Let $l_{i,t}$ and $k_{i,t}$ be the (log) number of employees and (log) capital of firms i at time t. For each firm

[6]The analysis of the growth dynamics of firms in terms of sales based on the same database analyzed here is extensively presented in Bottazzi and Secchi [forthcoming]

i consider the joint logarithmic rates of growth over a period τ of the number of employees and of the capital $(\Delta_\tau l_{i,t}, \Delta_\tau k_{i,t})$ where $\Delta_\tau x_i(t) = x_{i,t+\tau} - x_{i,t}$ with $x = \{l, k\}$. In order to provide a synthetic representation of the relation between these two variables we report in Figure 3 a binned scatter plot for 4 different sectors. These plots are built by dividing the observations in different quantiles according to $\Delta_\tau l_i(t)$ and plotting for each quantile the mean of $\Delta_\tau k_i(t)$ against the mean of $\Delta_\tau l_i(t)$. Visual inspection reveals that, especially when longer time horizon are considered ($\tau \geq 5$ years), a clear positive relationship emerges: as expected, the growth of a firm in terms of capital corresponds to a growth in terms of number of employees, and vice-versa. However, it is interesting to notice that on shorter time horizon ($\tau = 1$ year) the slope of the relation tends to change and become flatter. To analyze this effect from a quantitative point of view and to explore sectoral specificities in the relation between $\Delta_\tau k_i(t)$ and $\Delta_\tau k_i(t)$ without departing from the non-parametric approach, we calculate the cross correlation coefficient $\rho(\Delta_\tau k, \Delta_\tau l)$ for all the sectors and three different values of τ. Table 1 reports the results. The values obtained for $\rho(\Delta_\tau k, \Delta_\tau l)$ confirm the existence of a significant positive correlation between the firm growth expressed in terms of capital and in terms of labor, corroborating also the idea that the cross correlation coefficient is an increasing function of the length of the time-horizon. Notice that for all the sectors the difference between $\rho(\Delta_1 k, \Delta_1 l)$ and $\rho(\Delta_5 k, \Delta_5 l)$ is statistically significant[7] while considering $\rho(\Delta_5 k, \Delta_5 l)$ and $\rho(\Delta_9 k, \Delta_9 l)$ the same is true only in half of the sectors studied.

4 Parametric analysis

In this section we perform a parametric analysis of the input-output relations observed inside the different manufacturing sectors of our database. We describe the production activity in a two digit sector[8] with the help of a simple Cobb-Douglas production function (Cobb and Douglas [1928]). Output is proxied by sales S and we consider as inputs labor (i.e. number of employees) L and capital K to obtain the following functional relation

$$S = C\, L^\alpha\, K^\beta \quad . \tag{4}$$

where C is a constant term. Taking the logarithms, with usual notation, (4) becomes

$$s = \alpha\, l + \beta\, k + c \tag{5}$$

where $c = \log(C)$. The linear relation implied by the previous equation between log output and log inputs is, at least approximatively, consistent with the "planar" shapes shown in Fig 2. Notice that the specification in (5) does not impose homogeneity of degree 1 on the production function, thus allowing to test for the presence of different regimes of returns to scale. The parameters α and β represent the elasticity of output with respect to labor and capital, respectively.

Notwithstanding the simple functional form of (5), a variety of issues potentially arises in performing regression estimates of the input elasticities. In the next section we perform a simple cross-sectional ordinary least squares regression (OLS) of firms output on the different inputs, separately for each sector and in several different years. We start with an univariate analysis that takes in consideration a single input at a time and move, next, to the estimation of

[7]Here this means that $\rho(\Delta_5 k, \Delta_5 l)$ is greater than $\rho(\Delta_1 k, \Delta_1 l)$ plus two standard errors.

[8]Although the database allows to go as far as three-digit, we preferred to maintain a high number of observations in each sector.

SECTOR	ISIC Code	1989 Coeff.	1989 Std Err	1991 Coeff.	1991 Std Err	1994 Coeff.	1994 Std Err	1997 Coeff.	1997 Std Err
Food/Beverages	15	1.040	0.024	1.062	0.021	1.072	0.021	1.151	0.027
Textiles	17	1.053	0.025	1.074	0.022	1.146	0.023	1.181	0.025
Leather/Footwear	19	1.153	0.052	1.267	0.041	1.318	0.040	1.309	0.053
Wood Manufact.	20	1.195	0.047	1.180	0.044	1.283	0.044	1.299	0.048
Paper/Allied Prod.	21	1.084	0.030	1.114	0.027	1.143	0.034	1.197	0.034
Chemicals Prod.	24	1.158	0.020	1.119	0.019	1.067	0.019	1.151	0.022
Rubber/Plastics	25	1.024	0.023	1.043	0.022	1.108	0.022	1.134	0.026
Basic Metals	27	1.080	0.032	1.080	0.027	1.100	0.028	1.167	0.030
Metal Products	28	1.123	0.018	1.132	0.016	1.183	0.016	1.207	0.018
Indust. Machinery	29	1.063	0.011	1.078	0.011	1.107	0.011	1.135	0.012
Electr. Machinery	31	1.081	0.018	1.110	0.019	1.118	0.021	1.123	0.023
Furniture Manuf.	36	1.160	0.025	1.219	0.023	1.245	0.024	1.240	0.026

Table 2: Estimated slopes b_l of the regression $s \sim a_l + b_l\, l$ together with their standard errors.

the two inputs Cobb-Douglas production function defined in (5). In Section 4.2 we propose a different approach that uses the longitudinal dimension of our database to overcome some difficulties inherent in the OLS estimation. The idea is that repeated observations on a single firm allow to circumvent some of the problems that arise in a purely cross-sectional analysis. In particular, it is possible to identify those idiosyncrasies which reveal themselves as heterogeneity among firms and are relatively stable over the considered interval.

4.1 Production Function Estimates: Cross Sectional Analysis

We start our investigation with a simple univariate analysis of the relation between the output of a firm and the number of its employees. For each sector we consider the linear model

$$s_i = a_l + b_l\, l_i + \epsilon_i \quad , \tag{6}$$

where s_i and l_i stand, with usual notation, for the (log) sales and (log) number of employees of firm i and ϵ are i.i.d. random residuals. The intercept a_l and slope b_l are considered constant for all the firms in the same sector. The results of the regression of (6) for different years on the largest two-digit sectors are reported in Table 2. The observed slopes are never far from the value of 1 but, for several sector, they are significantly greater.

The same analysis can be repeated for the relationship between firm output and firm capital, fitting the model

$$s_i = a_k + b_k\, k_i + \epsilon_i \tag{7}$$

with k_i the (log) capital of the i-th firm. The results are reported in Table 3. The observed slopes are always significantly less than one, ranging from 0.6 to 0.8, apart from the last year, where a noticeable reduction can be observed. Indeed, in 1997 the slope b_k is characterized by values between 0.45 and 0.6.

As a second step we explicitly consider the multivariate dimension of the production process described by (5) and we estimate the elasticity of output with respect to both inputs. Following the Cobb-Douglas specification we consider the following regression

$$s_i = \omega + \alpha\, l_i + \beta\, k_i + \epsilon_i \quad , \tag{8}$$

where ϵ_i represents i.i.d. residuals. We estimate this model using OLS on a cross-section of firms in a given year. In Table 4 we report the estimated values of α and β for the different two-digit sectors. As in the univariate case, we report results for different years so as to provide

SECTOR	ISIC	1989		1991		1994		1997	
	Code	Coeff.	Std Err	Coeff.	Std Err	Coeff.	Std Err	Coeff.	Std Err
Food/Beverages	15	0.748	0.017	0.744	0.015	0.681	0.015	0.574	0.015
Textiles	17	0.620	0.014	0.610	0.013	0.598	0.011	0.513	0.015
Leather/Footwear	19	0.696	0.019	0.672	0.018	0.693	0.017	0.561	0.024
Wood Manufact.	20	0.662	0.028	0.662	0.023	0.658	0.022	0.496	0.026
Paper/Allied Prod.	21	0.692	0.019	0.692	0.017	0.667	0.019	0.524	0.021
Chemical Prod.	24	0.743	0.017	0.735	0.017	0.706	0.018	0.601	0.018
Rubber/Plastics	25	0.726	0.016	0.708	0.015	0.660	0.015	0.546	0.016
Basic Metals	27	0.866	0.019	0.811	0.017	0.793	0.019	0.641	0.021
Metal Products	28	0.654	0.012	0.640	0.011	0.603	0.009	0.443	0.011
Industr. Machinery	29	0.687	0.011	0.635	0.011	0.628	0.010	0.558	0.011
Electr. Machinery	31	0.701	0.014	0.687	0.014	0.661	0.014	0.577	0.017
Furniture Manuf.	36	0.590	0.017	0.608	0.015	0.591	0.015	0.477	0.017

Table 3: Estimated slopes b_k of the regression $s \sim a_k + b_k\, k$ together with their standard errors.

an account of possible trends in time. Comparison of parameters at different years point out a relative stability of the estimates. The only change which appears at a first glance is the decrease of the capital elasticity, β, as time increases, confirming the results of the univariate analysis (see Table 3). The reduction in the value of β is more apparent in the more recent years of the considered interval and seems to imply that, *ceteris paribus*, the contribution to total output of additional investments in the recent years of the interval would be less effective than at the beginning of the period. This finding would deserve further investigations, which goes far beyond the purpose of the present study. Here it suffices to say that the short time span in which the trend gets disclosed would suggest other causes than inflation. The relatively sudden decrease in coefficients in nearly all sectors could hint at effects which are due to a change in the institutional setting of the market. In particular, a possible explanation for this distortion could be found in the Italian Tremonti's law, which enabled firms to benefit from partial tax exemption for profits re-invested in the corporate business. The law fostered investments and plants renewal but the new capital goods were not immediately productive. Tremonti's law was in force for 1994 and 1995 only, but economic consequences clearly outlived the norm itself.

With respect to intra-sectoral heterogeneity, the different magnitude in the coefficients accounts well for the required peculiarity of the production process in different manufacturing sectors. From Table 4 it is also evident that the sum of elasticities of labor and capital is close to one in almost all sectors, hinting at a general presence of a constant return to scale effect in production. Among exceptions, however, we mention Chemical Products (ISIC 24) and Industrial Machinery (ISIC 29). On the other hand, Furniture Manufacturing (ISIC 36) needs a more detailed investigation, since it also comprises most of the firms which were left out from the considered classification of industrial sectors. The robustness of the approximately constant returns to scale structure is confirmed by the fact that when the elasticity of capital, β, decreases, a counterbalancing effect is very often observed which leads to an increase in the labor elasticity α.

4.2 Production Function Estimates: Panel Data Analysis

As it has been early noticed (Mendershausen [1938], Marschak and Andrews [1944]) the estimation of production function from cross-sectional empirical data can plausibly be affected by a problem of simultaneity. It may indeed happen that observed inputs (i.e. labor and capital) are correlated with unobserved ones. Thus, the decision process of inputs adoption performed by firms is affected by variables not available to the economist. The existing correlation be-

SECTOR	ISIC Code	1989			1991			1994			1997		
		c	α	β	c	α	β	c	α	β	c	α	β
Food and Beverages	15	3.715	0.584	0.424	3.778	0.612	0.408	4.067	0.702	0.344	4.300	0.733	0.318
		(0.132)	(0.034)	(0.024)	(0.123)	(0.030)	(0.021)	(0.118)	(0.028)	(0.019)	(0.111)	(0.029)	(0.015)
Textiles	17	3.537	0.613	0.361	3.633	0.635	0.337	3.537	0.623	0.373	4.03	0.886	0.203
		(0.100)	(0.029)	(0.017)	(0.098)	(0.030)	(0.017)	(0.091)	(0.029)	(0.015)	(0.113)	(0.034)	(0.018)
Leather - Footwear	19	2.994	0.473	0.546	2.923	0.638	0.464	2.883	0.649	0.493	3.256	0.855	0.348
		(0.149)	(0.047)	(0.025)	(0.138)	(0.046)	(0.022)	(0.131)	(0.044)	(0.021)	(0.187)	(0.056)	(0.026)
Wood Manufact.	20	3.010	0.735	0.369	3.023	0.637	0.416	3.033	0.722	0.397	3.806	0.968	0.206
		(0.187)	(0.059)	(0.033)	(0.162)	(0.052)	(0.028)	(0.161)	(0.054)	(0.027)	(0.188)	(0.062)	(0.028)
Paper & Allied Prod.	21	3.626	0.573	0.396	3.629	0.609	0.374	3.739	0.620	0.372	4.380	0.873	0.205
		(0.133)	(0.042)	(0.027)	(0.125)	(0.042)	(0.026)	(0.151)	(0.051)	(0.029)	(0.142)	(0.045)	(0.022)
Chemicals Prod.	24	3.688	0.829	0.274	4.088	0.840	0.238	4.572	0.816	0.226	4.617	0.881	0.208
		(0.117)	(0.033)	(0.022)	(0.121)	(0.032)	(0.023)	(0.128)	(0.031)	(0.022)	(0.114)	(0.029)	(0.018)
Rubber Plastics	25	3.461	0.547	0.422	3.501	0.613	0.380	3.663	0.694	0.342	4.072	0.800	0.266
		(0.117)	(0.032)	(0.022)	(0.111)	(0.030)	(0.020)	(0.105)	(0.030)	(0.018)	(0.108)	(0.030)	(0.016)
Basic Metals	27	2.475	0.300	0.676	2.877	0.466	0.525	3.279	0.554	0.462	3.982	0.794	0.297
		(0.178)	(0.048)	(0.036)	(0.151)	(0.040)	(0.029)	(0.170)	(0.044)	(0.031)	(0.145)	(0.038)	(0.022)
Metal Products	28	3.330	0.725	0.329	3.399	0.775	0.294	3.334	0.776	0.317	3.975	0.976	0.171
		(0.076)	(0.023)	(0.014)	(0.072)	(0.022)	(0.013)	(0.064)	(0.019)	(0.010)	(0.073)	(0.022)	(0.010)
Indust. Machinery	29	4.217	0.850	0.185	4.450	0.953	0.108	4.487	0.963	0.121	4.622	0.984	0.117
		(0.066)	(0.019)	(0.014)	(0.063)	(0.018)	(0.013)	(0.062)	(0.018)	(0.012)	(0.062)	(0.018)	(0.011)
Electr. Machinery	31	3.608	0.723	0.307	3.588	0.742	0.307	3.782	0.703	0.323	4.275	0.828	0.231
		(0.084)	(0.026)	(0.018)	(0.086)	(0.027)	(0.017)	(0.093)	(0.030)	(0.018)	(0.101)	(0.030)	(0.017)
Furniture Manufact.	36	3.568	0.855	0.249	3.413	0.903	0.252	3.495	0.927	0.248	4.110	1.008	0.154
		(0.104)	(0.032)	(0.018)	(0.096)	(0.030)	(0.017)	(0.097)	(0.031)	(0.017)	(0.108)	(0.032)	(0.016)

Table 4: Elasticity of Output with respect to Capital and Labor. Estimated parameters of the regression: $s_t = c + \alpha\, l_t + \beta\, k_t$. Standard errors in brackets.

tween the unobserved variables and the regressors introduces biases in OLS estimators of the production function parameters. For instance, considering the Cobb-Douglas specification previously introduced one can write

$$s_i = \alpha l_i + \beta k_i + \omega_i + \epsilon_i \quad , \tag{9}$$

where ϵ_i are i.i.d. components and where ω_i represents unobserved inputs like managerial ability, quality of land or materials which affect firm output s_i. The coefficient c in (5) has been split in two components: a stochastic part, ϵ_i, that might represent measurement error in output or any shock affecting output which is unknown to the firm itself when making choices for capital and labor, and ω_i, a structural part of firms activity, which is known to the firm when it plans its production activity, but which is ignored by the economist. If the observed inputs, l_i and k_i, are correlated with the unobserved ω_i, the OLS estimators of the coefficients α and β will result biased. The purpose of the following panel data analysis is to employ at the same time the cross sectional and time series dimensions of our database to overcome, at least partly, these difficulties. Indeed certain "unobserved" inputs, such as quality of materials or entrepreneurial ability, can be considered, in first approximation, fixed over time and thus can be eliminated by applying appropriate "within" transformations. Rewriting (9) in panel data notation, introducing an explicit dependence on time t, we obtain the following

$$s_{i,t} = \alpha\, l_{i,t} + \beta\, k_{i,t} + \omega_i + e_{i,t} \quad . \tag{10}$$

In the following analysis we will consider three different models, based on (10), which enable to account for possible sources of heterogeneity among firms in each of the considered sectors. In this way we are able to evaluate the sensitiveness of coefficient estimates to the chosen specification. First we estimate the *fixed effects model* where ω_i are considered time invariant so that can be eliminated by subtracting the individual mean to obtain the model

$$(s_{it} - \bar{s}_i) = \alpha\,(l_{it} - \bar{l}_i) + \beta\,(k_{it} - \bar{k}_i) + (e_{i,t} - \bar{e}_i) \quad , \tag{11}$$

where the notation $\bar{x}$ stands for individual average of quantity x over time. This approach was first exposed in Hoch [1958], and then popularized by Mundlak [1961]. A second alternative specification is obtained by considering the variability between individuals and neglecting that within individuals, to obtain the *between-group model* (Wooldridge [2002]) defined by the following relation

$$\bar{s}_i = \alpha \bar{l}_i + \beta \bar{k}_i + \omega_i + \bar{e}_i \quad , \tag{12}$$

where $\omega_i + \bar{e}_i$ is now the error term. As we are now including individual effects in the error terms, we need to assume they are uncorrelated with the explanatory variable l and k. Finally, we consider the *random effects model* where the individual specific effects ω_i, as opposed to the fixed effects model where they are considered deterministic and constant over time, are assumed to be random variables. The issue is whether or not ω_i can be considered as random draws from a common population or whether the conditional distribution of ω_i given the regressors, l and k, can be viewed as identical across i. For a more detailed exposition we refer the reader to Hsiao [2003]. As far as the present work is concerned, it suffices to bear in mind that the random effect estimator is a (matrix) weighted average of the estimates produced by the between and within (or fixed) estimators. The results for the different estimates are reported in Table 5, where for the *random effects model* we consider both Generalized Least Squares (GLS) and Maximum Likelihood (ML) estimations.

The estimated parameters of the fixed effect model suggest a relatively smaller capital elasticity for most sectors, when compared to OLS estimates in Table 4. This result is common to large part of panel data applications to production function estimates (see for instance the discussion in Griliches and Mairesse [1995]). Nevertheless, the coefficients' estimates we obtained do not bear other bad features pointed out in the literature. In particular, our panel data estimates of elasticities of output with respect to capital, although significantly lower than the ones obtained with OLS, are still statistically significant. Further, the resulting estimates of returns to scale do not display a sharp decrease as reported, for instance, by Griliches and Mairesse [1995]. Estimated coefficients of the random effects model with GLS and ML are closer for sectors with more observations; the two estimators, indeed, converge asymptotically. Notice that the Hausman test (Hausman [1978]) for model specification rejects the hypothesis that the individual-level effects are adequately modeled by a random effects specification. However, this does not exclude the appropriateness of the random effects model under a different specification of the production process, for instance.

4.3 Testing for constant output elasticity

We conclude our parametric investigation proposing a comparison between a standard exercise in production theory and our empirical data. We use the Cobb-Douglas production function introduced before, which is known to fit well inside the domain of the standard (*neoclassical*) production theory. Let us assume, as in many textbooks in microeconomics, that the firm chooses its production activity solving a cost minimization problem. Specifically, assume that the firm knows that its present market share grants it a level of output equal to S, so that the choice of the level of labor L and capital K is the solution of the following problem

$$\min_{L,K}\{L\, p_L \, + K\, p_K\} \qquad \text{s. t.} \qquad c\, L^\alpha\, K^\beta = S \quad , \tag{13}$$

where p_L and p_K are the unit cost of labor and capital, respectively. Solving the problem one obtains the following conditional factor demand equations for labor L

$$L(p_L, p_K, S) = S^{1/(\alpha+\beta)} c^{-1/(\alpha+\beta)} \left(\frac{\alpha}{\beta}\frac{p_K}{p_L}\right)^{\beta/(\alpha+\beta)} \quad ,$$

and capital K

$$K(p_L, p_K, S) = S^{1/(\alpha+\beta)} c^{-1/(\alpha+\beta)} \left(\frac{\beta}{\alpha}\frac{p_L}{p_K}\right)^{\alpha/(\alpha+\beta)} \quad .$$

Considering the input ratio r, expressed as capital per unit of labor

$$r = \frac{K}{L} = \frac{\beta}{\alpha}\frac{p_L}{p_K} \quad ,$$

and taking the logarithms one has, with usual notation,

$$s = \beta\, \log(r) + (\alpha+\beta)\, l \tag{14}$$

and

$$s = -\alpha\, \log(r) + (\alpha+\beta)\, k \quad . \tag{15}$$

Thus, if inputs are chosen according to (13), the input ratio does not depend on the actual size of the firm and the elasticity of output with respect to inputs reduces to $\alpha+\beta$.

SECTOR	ISIC Code	Total Obs.	Fixed Effects (Within-group)			Between-group			Random Effects (ML)			Random Effects (GLS)		
			c	α	β	c	α	β	c	α	β	c	α	β
Food and Beverages	15	11715	5.817	0.432	0.268	4.093	0.731	0.325	5.114	0.568	0.282	5.098	0.571	0.282
			(0.064)	(0.014)	(0.005)	(0.093)	(0.023)	(0.015)	(0.053)	(0.012)	(0.005)	(0.051)	(0.011)	(0.005)
Textiles	17	15423	5.534	0.565	0.149	3.532	0.674	0.342	4.821	0.654	0.185	4.783	0.658	0.190
			(0.057)	(0.013)	(0.005)	(0.075)	(0.025)	(0.012)	(0.049)	(0.011)	(0.005)	(0.047)	(0.011)	(0.005)
Leather - Footwear	19	8736	4.575	0.737	0.193	2.756	0.707	0.466	3.841	0.818	0.244	3.802	0.821	0.248
			(0.088)	(0.022)	(0.007)	(0.105)	(0.035)	(0.015)	(0.072)	(0.018)	(0.006)	(0.069)	(0.018)	(0.006)
Wood Manufact.	20	11715	4.734	0.692	0.191	3.261	0.743	0.353	4.232	0.758	0.221	4.217	0.760	0.222
			(0.103)	(0.025)	(0.009)	(0.135)	(0.045)	(0.021)	(0.084)	(0.021)	(0.008)	(0.082)	(0.021)	(0.008)
Paper & Allied Prod.	21	4475	5.065	0.687	0.189	4.030	0.633	0.335	4.598	0.749	0.215	4.603	0.749	0.215
			(0.125)	(0.030)	(0.009)	(0.116)	(0.039)	(0.021)	(0.083)	(0.021)	(0.008)	(0.082)	(0.021)	(0.008)
Chemicals Prod.	24	7189	5.030	0.654	0.242	3.672	0.802	0.309	4.274	0.763	0.260	4.280	0.762	0.260
			(0.089)	(0.019)	(0.007)	(0.092)	(0.025)	(0.016)	(0.062)	(0.014)	(0.006)	(0.061)	(0.014)	(0.007)
Rubber Plastics	25	8950	4.799	0.672	0.215	3.758	0.683	0.335	4.368	0.724	0.243	4.372	0.724	0.243
			(0.074)	(0.017)	(0.007)	(0.082)	(0.023)	(0.014)	(0.054)	(0.013)	(0.006)	(0.053)	(0.013)	(0.006)
Basic Metals	27	5190	4.273	0.796	0.238	3.801	0.702	0.335	4.140	0.792	0.255	4.141	0.793	0.255
			(0.125)	(0.026)	(0.010)	(0.126)	(0.033)	(0.022)	(0.082)	(0.018)	(0.009)	(0.082)	(0.018)	(0.009)
Metal Products	28	20591	4.331	0.858	0.155	3.630	0.820	0.262	4.009	0.881	0.184	4.010	0.881	0.184
			(0.052)	(0.012)	(0.004)	(0.051)	(0.016)	(0.008)	(0.036)	(0.009)	(0.004)	(0.036)	(0.009)	(0.004)
Indust. Machinery	29	21965	4.632	0.875	0.142	4.552	0.934	0.124	4.552	0.901	0.140	4.553	0.901	0.141
			(0.054)	(0.012)	(0.005)	(0.047)	(0.014)	(0.009)	(0.033)	(0.008)	(0.004)	(0.034)	(0.008)	(0.004)
Electr. Machinery	31	8409	5.182	0.718	0.133	3.562	0.768	0.305	4.250	0.815	0.190	4.241	0.815	0.191
			(0.077)	(0.017)	(0.007)	(0.063)	(0.021)	(0.012)	(0.050)	(0.013)	(0.007)	(0.048)	(0.012)	(0.006)
Furniture Manufact.	36	13061	4.936	0.704	0.165	3.523	0.917	0.247	4.386	0.803	0.186	4.378	0.805	0.186
			(0.062)	(0.015)	(0.005)	(0.078)	(0.025)	(0.013)	(0.050)	(0.012)	(0.005)	(0.048)	(0.012)	(0.005)

Table 5: Estimated coefficients for the Fixed Effects, Between-group and Random effects model (both Maximum Likelihood and GLS Estimates). Standard Errors in brackets.

SECTOR	ISIC Code	1989 Coeff.	1989 Std Err	1991 Coeff.	1991 Std Err	1994 Coeff.	1994 Std Err	1997 Coeff.	1997 Std Err
Food/Beverages	15	0.236	0.018	0.253	0.018	0.247	0.018	0.462	0.028
Textiles	17	0.377	0.020	0.389	0.018	0.477	0.017	0.379	0.026
Leather/Footwear	19	0.480	0.026	0.484	0.024	0.470	0.020	0.450	0.038
Wood Manufact.	20	0.364	0.035	0.455	0.034	0.466	0.031	0.461	0.049
Paper/Allied Prod.	21	0.420	0.033	0.430	0.029	0.442	0.029	0.524	0.048
Chemical Prod.	24	0.235	0.019	0.216	0.021	0.187	0.022	0.323	0.032
Rubber/Plastics	25	0.292	0.021	0.298	0.022	0.350	0.022	0.414	0.032
Basic Metals	27	0.289	0.019	0.294	0.021	0.276	0.021	0.366	0.037
Metal Products	28	0.345	0.017	0.328	0.017	0.427	0.016	0.419	0.026
Industr. Machinery	29	0.189	0.014	0.166	0.014	0.193	0.013	0.252	0.019
Electr. Machinery	31	0.271	0.020	0.312	0.022	0.384	0.023	0.372	0.033
Furniture Manuf.	36	0.301	0.023	0.318	0.021	0.321	0.020	0.312	0.030

Table 6: Estimated slope a_r of the regression in (16) together with its standard error.

This prediction is clearly violated by the estimates reported in Tables 2 and 3. Indeed, leaving aside the intercept, the estimated slopes for output-labor and output-capital relations in equations (6) and (7) are significantly different in all sectors under analysis. This issue can be further clarified by running a cross-sectional regression of inputs ratio r versus firm (log) size

$$log(r) \sim a_r + b_r\, s \quad . \tag{16}$$

The results are reported in Table 6. As can be seen, the slope coefficients a_r are significantly different from zero in each year and in each sector under study. The scatter plot of the inputs ratio versus output for the firms in four different sectors are presented in Fig. 4, together with the linear fit provided by (16). For the sake of clarity, in these plots observations have been binned in several quantiles, nevertheless all the available observations have been employed while performing the relative regressions. The high significance of the estimated slope coefficients a_r reported in Table 6 clearly appears in Fig. 4. In all the sectors, although with different intensities, the mix of inputs tends to substitute labor for capital as size increases. This result suggests that the conjecture of a constant input mix for different level of output is, for the Italian Manufacturing sectors, not appropriate.

5 Conclusions

The aim of this work was to propose a summary description of how the production process is conducted in the different sectors of the Italian manufacturing industry. We tried to accomplish to this by combining an exploratory, non-parametric analysis together with an, admittedly oversimplified, model of the sectoral production function. The non-parametric analysis allowed us to identify and describe some of the salient properties which characterize, *de facto*, the way production is carried out. At the same time, we tried to lay down an empirically testable framework in which some standard assumptions of what is generally accepted as production theory can be studied.

The non-parametric analysis reveals that the production process displays a heterogenous nature: it is possible to attain a certain level of output with various mix of capital and labor. This hints at the presence of a non-negligible rate of substitutability, at least when these two factors of production are considered, in actual production technologies. This result also leaves room for the coexistence, in the same sector, of firms that adopt very different procedures, possibly also from an organizational perspective, to carry out production. At the same time, heterogeneity also gets disclosed through the remarkably different levels of technical efficiency,

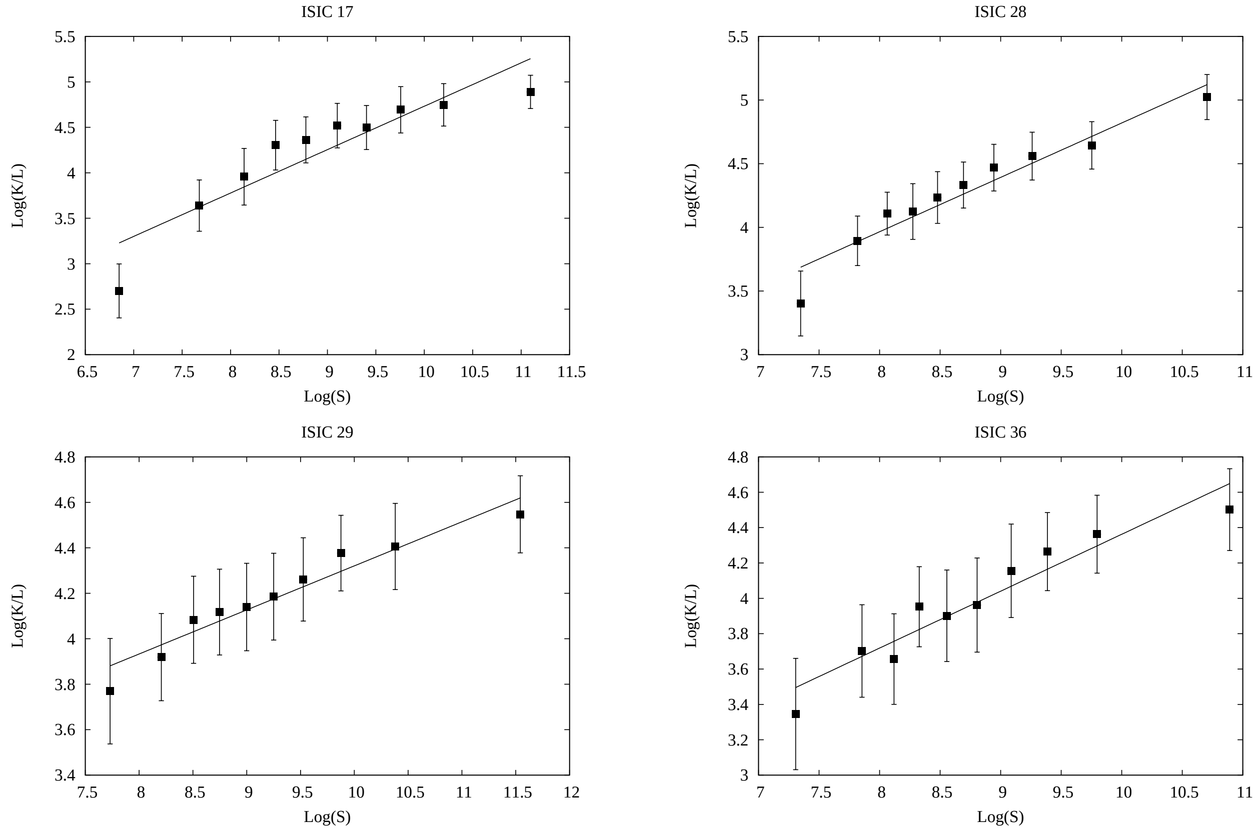

Figure 4: Relation between output and input ratio, k/l: binned scatter plots in 4 sectors in 1994. Errorbars display two standard errors.

here proxied by labor and capital productivities, attained by firms in the same sectors (see Figure 1). With this respect, it seems that markets for manufactured goods tolerate firms whose productivity is and remains substantially different over time.

Results on cross-sectional observations (see Table 4) lend support to the conjecture of high sectoral stability of the technical coefficients over time. The panel data analysis, even if in several cases provides significantly different results, globally confirms the same behavior (see Table 5). This empirical evidence is also supported by theoretical reasoning; indeed, the nature of the production process, especially in traditional manufacturing sectors, does not seem to leave much room for sudden changes in the way production is carried out. It is also true, however, that unexpected factor price fluctuations or a new institutional setting might well cause a sudden shift in inputs usage and, consequently, in estimated elasticity coefficients. In any case, it is natural to expect that existing plants, established technologies and organizational routines will tend to hamper not only adoption of new technologies, but also a rethinking of the way the production process is managed (Nelson and Winter [1982]). Finally, the evidence of input ratio that varies with size, provided by Table 6 and Fig. 4, may be due to input prices depending on the scale of activity and/or to firm operating with different technology at different size classes. The analysis performed in this work does not allow us to discriminate the two causes.

The main goal of this work rests in seeking to propose an empirically-based approach in the domain of production theory. The observed regularities, should, in no way, be interpreted as hinting at the presence of some “natural” and “unmodifiable” laws, rather they are the results of an ongoing process which bears the consequences of being highly specific in space and time. However, we believe that any model who aims to propose a description of corporate production activity has to encompass, at least at a bare bones level, some of the features which are disclosed in the present analysis.

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