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Recent Developments in Productivity and the Role of Entrepreneurship in Italy: An Industry View

Andrea Brasili - Loredana Federico*
UniCredit Group, Milan

This paper explores the existing interplay between productivity trends across Italian industries, in the decade 1995-2005, and entrepreneurship, highlighting the urgent need for a revival in entrepreneurial capital in some industries. Initially, we consider as a measure of entrepreneurship the birth rates for different industries; this proxy proved to be a significant explanatory variable of a sector's efficiency. We then attempt to extract a measure of managerial ability directly from the data, considering it as an unobservable and using Bayesian techniques to perform the estimation, which further reinforces the previous results. [JEL Classification: L26; O43; O47; C11]

Key words: entrepreneurship, productivity growth, stochastic frontiers, Bayesian analysis, Gibbs sampling.

1. - Introduction

Tentative explanations of Italy's disappointing productivity performance over the last ten years have highlighted various special features of the Italian economy, including the issues of specialisation, production fragmentation, and the lack of commitment to R&D. All of these explanations are in some ways true, but do not resolve the questions of their origins and their persistency. The aim of this paper is to analyse the role of entrepreneurship capital in this respect and to explore the existing interplay between productivity trends and entrepreneurship. The

* *<Andrea.Brasili@unicreditgroup.eu>; <Loredana.Federico@unicreditgroup.eu.>.*
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importance of its role is also apparent from a policy perspective, as evidenced by the publication a few years ago of a Green Paper by the European Commission on this subject.

The paper is organised as follows: Section 2 provides the backdrop, discussing recent trends in productivity growth in Italy. By taking an industry view, we can explore themes like the different performances of ICT-using and -producing sectors, or non-ICT industries[1], and via Roeger's method, mark-up estimations, which show a link between sectors experiencing low productivity growth and those characterised by high mark-ups, confirming that the lack of competitive pressures is an issue. This introduces our discussion of the need for a revival in entrepreneurship capital, which continues in Section 3. Here, we adapt the definition of entrepreneurial capital proposed by Audretsch and Keilbach (2003, 2004) to an industry view; with this measure (an index more than a direct measure), we run an estimation of a typical model developed in papers on productivity and technical efficiency, known as Stochastic Frontier Analysis (hereafter SFA), where this measure is used to explain differences in efficiency in different industries.

In Section 4, the analysis is brought one step forward, and we attempt to extract information on entrepreneurship capital from data, considering it as an unobservable variable and resorting to Bayesian analysis. By adopting a fully Bayesian approach to estimating a stochastic frontier model with random coefficients, we need to obtain the posterior marginal distribution of the unobserved random components (efficiency components and random coefficients) as well as the joint posterior distribution of all constant parameters, depending on the model and data. The Markov Chain Monte Carlo (henceforth MCMC) method that allows us to simulate all these marginal distributions efficiently is Gibbs sampling combined with data augmentation (Geman and Geman, 1984; Tanner and Wong, 1987; Gelfand and Smith, 1990). We refer to Kim and Nelson (1999), Geweke (1999) and Chib (2001) for an illustration of MCMC methods and to Koop (2003)

[1] ICT stands for Information and Communication Technology.

for Bayesian inference in stochastic frontier models. We draw some conclusions in Section 5.

2. - The Recent Productivity Slowdown: A Detailed Exploration

Changes in productivity are key to explaining economic performance. Looking at trends in labour productivity and real GDP in the Eurozone over the last decade, we cannot dismiss the view that potential GDP growth (and, at least in some ways, economic well-being) and productivity growth are strongly intertwined, even considering the latter's usual pro-cyclicality; macroeconomic output and productivity per person employed have shown a very similar declining trend; moreover, remarkably, the trend in labour productivity in the Eurozone has been trending downwards constantly since 1992.

A comparison of aggregate national accounts data[2] shows that real GDP growth in the Eurozone has constantly underperformed that of the United States since 1992, but labour productivity (computed as output per person employed) only started to rise more rapidly in the United States than in the Eurozone in the mid 1990s, widening the productivity gap between the two areas. Italy's performance in terms of GDP growth, and even more in terms of labour productivity, has been the worst in the area, particularly from 2001 to 2005.

The relation between overall economic growth and labour productivity growth is fairly straightforward. In pure accounting terms, real gross domestic product can be broken up into employment, as a proxy for labour input, and productivity per person employed.

As we can see from Table 1, employment growth in the Eurozone has progressively recovered since the beginning of the 1990s, and picked up strongly in the second half of the decade (an acceleration of 2.1% in 1996-2000 compared to the first five years). Subsequently,

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[2] Based on the European Commission - AMECO Database.

the employment growth rate saw a slight trend reversal over the period 2001-05, but remained higher than in the United States. However, good news on the employment side has been more than offset by the progressive deterioration in labour productivity. Labour productivity has been trending downwards since the mid 1990s, with meagre growth of 0.5% in 2001-2005. An opposite pattern emerged in the United States, where a steady and then upward trend in employment (with the exception of the slowdown in 2001 and 2002) was accompanied by an upsurge in labour productivity. Since the mid 1990s, labour productivity in the United States has increased constantly, recording an average growth rate of 2.0%.

Furthermore, following the traditional Solow's growth accounting approach,[3] labour productivity growth breaks down into two main components: the change in the amount of capital available per worker (the capital-labour ratio or weighted capital deepening), which accounts for the fact that workers are more productive when they have more or better physical capital to work with, and the variation in the total factor productivity (TFP), which reflects the overall efficiency with which inputs are turned into output and can be regarded as a gauge of technical progress, the contribution of economies of scale, allocative efficiency, and lastly, time-variant technical efficiency.[4] The outcome of this breakdown in 1992-2006 is reported in Table 1.

As Table 1 shows, the Eurozone's three largest economies experienced a decline in labour productivity, but in Italy in the period 2001-2005, aggregate data point to a decline in productivity that, given a slight capital deepening, implies an even greater decline in total factor productivity, denoting an extraordinary technical regress in the Italian economy.

While numerous analyses have investigated the structural weaknesses of the Italian economy (the most frequently cited being the very small average size of companies, persistent specialisation in low tech, low demand growth sectors, and linked to this, the absence

[3] See Barro R.J. - Sala-I-Martin X. (2003).

[4] We refer to Kumbhakar S.C. - Knox Lovell C.A. (2000) for a technical discussion about the decomposition of the total factor productivity change into its various sources.

TABLE 1

EMPLOYMENT, LABOUR PRODUCTIVITY AND TFP (1992-2006)
Annual rates, in percent

	1992-1995	1996-2000	2001-2005	2006
United States				
GDP	3.2	4.1	2.4	3.3
Employment	1.6	2.0	0.7	1.9
Labour Productivity	1.5	2.1	1.7	1.4
TFP	1.3	1.6	0.9	0.8
Capital Deepening	0.3	0.5	0.9	0.6
Eurozone (12)				
GDP	1.4	2.7	1.4	2.7
Employment	-0.6	1.5	0.9	1.4
Labour Productivity	2.0	1.2	0.5	1.2
TFP	1.1	0.9	0.1	1.0
Capital Deepening	0.8	0.2	0.4	0.2
Germany				
GDP	1.5	2.0	0.6	2.7
Employment	-0.7	0.8	-0.2	0.7
Labour Productivity	2.2	1.2	0.8	1.9
TFP	1.2	0.8	0.4	1.8
Capital Deepening	1.0	0.4	0.4	0.1
France				
GDP	1.2	2.8	1.5	2.0
Employment	-0.2	1.4	0.6	0.8
Labour Productivity	1.4	1.4	0.9	1.1
TFP	0.7	1.2	0.4	0.7
Capital Deepening	0.7	0.2	0.5	0.5
Italy				
GDP	1.2	1.9	0.7	1.9
Employment	-1.5	1.0	1.5	1.4
Labour Productivity	2.7	0.9	-0.8	0.5
TFP	1.7	0.7	-0.9	0.4
Capital Deepening	0.9	0.2	0.1	0.1

Capital and labour are estimated as averages for the period.

of or insufficient investment in R&D by the private sector), some very recent analyses have raised doubts about the actual situation. Among them, De Nardis (2007) suggests that scraping the surface of aggregate data reveals a wide variety of particular behaviour patterns and a great deal of restructuring activity; and even if aggregate production has been shrinking, there has been a not insignificant number of success stories among Italian firms. Moreover, it also highlights that part of the productivity story is due to a change in production techniques prompted by a change in the actual costs of input factors (due to the labour market reforms of 1997-2000).

At present, as Table 1 suggests, 2006 data imply a clear improvement. Hence, one and a half years out of the Italian economy's long sluggish period of 2001-2005, it seems that those who did not embrace the view that Italy was bound to progressively lose its status in the top class of developed economies have to some extent been vindicated. Nonetheless, it is difficult to dismiss the view that some structural problems are present, and are likely to remain.

The truth, as frequently happens, probably lies somewhere in the middle, and the two arguments are not in the least opposed. Some more disaggregated analyses show how they are reconciled. Disaggregation is worth following in firms' balance-sheet data or at sector level data; in this paper, we follow this second route.

Calculating labour productivity at an industry level[5] is instructive, and suggests that the true problem (*i.e.* the labour productivity slowdown) is not in ICT-producing sectors, which benefited from recent technological advances also in Italy, but in ICT-using and non-ICT sectors (the results are shown in Table 2).

[5] The dataset for this study is the 60-Industry Database of the Groningen Growth and Development Centre (GGDC). In detail, all industry sectors, manufacturing and services, are divided into ICT-producing sectors (*e.g.* Office machinery in manufacturing, and Communications in services) and intensive ICT-using sectors, *i.e.* industries which make wide use of ICT (*e.g.* Printing & publishing, Mechanical engineering in manufacturing, Wholesale and retail trade and Financial intermediation in services). All remaining sectors are classified as non-ICT sectors (*e.g.* Food, drink & tobacco, Education, Agriculture and Building). The distinction between ICT-producing and ICT-using sectors is of interest, because positive spillover effects from the use of ICT should emerge in sectors other than the ICT-producing sectors themselves, and emphasises the importance of the use of ICT. See O'MAHONY M. - VAN ARK B. (2003) and ESTEVAO M.M. (2004, p. 33).

Table 2

ITALIAN LABOUR PRODUCTIVITY
GROWTH BY ICT CLASSIFICATION (1992-2003)
(in percent, at an annual rate)

	1992-1995	1996-2000	2001-2003	% shares VA 2003
Italy				
Total economy	2.6	1.0	-0.6	100.0
ICT-producing industries	6.4	7.2	3.0	4.8
ICT-producing manufacturing	9.6	14.7	0.0	0.8
ICT-producing services	5.4	4.6	3.7	4.0
ICT-using industries	3.0	1.7	-0.7	29.6
ICT-using manufacturing	4.4	1.4	-1.7	6.2
ICT-using services	2.4	1.7	-0.5	23.4
Non-ICT industries	2.2	0.2	-0.7	65.5
Non-ICT manufacturing	3.5	0.6	-0.6	11.8
Non-ICT services	1.5	-0.6	-1.0	43.4
Non-ICT-other	2.8	2.4	0.0	10.3

As a further confirmation of these results, Table 3 shows the best and worst performers among Italian industries, confirming that structural weaknesses seem to be more in transmission and diffusion (once strengths of the Italian economy) than in knowledge or technology creation.

Transmission and diffusion are categories related to the competitive environment at large, hence we thought it relevant to look at a traditional but still very informative measure of market power: the mark-up.[6]

Indeed, entrepreneurs with a high market power are likely to be less prone to restructuring and introducing innovations in their

[6] By adding price information to the previous analysis, in Table 4, we provide estimates of mark-ups of product prices over marginal costs for manufacturing and service industries over the 1981-2005 period. The estimates are based on the methodology put forward by Roeger W. (1995). In this context, the analysis is extended to include intermediate inputs, as it allows several bias characterising measures that only consider labour and capital as production factors to be bypassed. Further details on mark-up estimates are available on request.

TABLE 3

A SNAPSHOT OF DIFFERENT ITALIAN INDUSTRIES

	Sector	NACE Code	Labour productivity growth *(in percent, annual rates)*		
			1992-1995	1996-2000	2001-2003
Best performers					
Office machinery	ICT- Producing manufacturing	(30)	37.6	50.6	55.6
Communications	ICT-Producing services	(64)	8.6	8.8	10.0
Worst performers					
Computer and related activities	ICT-Using services	(72)	0.6	0.7	-0.7
Wholesale trade	ICT-Using services	(51)	5.9	0.0	-0.7
Retail trade	ICT-Using services	(52)	0.8	1.2	-0.8
Financial intermediation	ICT-Using services	(65)	1.6	5.4	-2.2
Research and development	ICT-Using services	(73)	1.5	5.8	-7.9
Food, drink & tobacco	Non-ICT manufacturing	(15-16)	2.5	0.9	0.2
Textiles	Non-ICT manufacturing	(17)	2.4	0.9	-2.0
Basic metals	Non-ICT manufacturing	(27)	8.0	-1.4	-2.6
Sale, maintenance and repair	Non-ICT services	(50)	6.2	0.4	-1.3
Hotels & catering	Non-ICT services	(55)	-0.9	0.0	-4.7
Private households	Non-ICT services	(95)	1.1	-0.2	-3.7

business, promoting slower changes to the total productivity of factors (the so-called dynamic efficiency).

The results reported in Table 4 are consistent with our *a priori* views about the degree of competitiveness in each sector, and suggest that differences in estimated mark-ups affect the estimated growth rates of total factor productivity.[7]

In fact, Tables 3 and 4 show that in some cases, sectors with a great mark-up ratio also registered a fairly poor performance in terms of labour productivity. Hence, the whole picture seems to suggest that the economy is affected by difficulties in generating and spreading best practice, and simultaneously but not independently, by a relatively low level of competitive pressures. In this respect, it seems quite clear that a significant injection of entrepreneurial energy could be of benefit in relation to both these issues.

3. - The Need for a Revival in Entrepreneurial Capital

It appears that one of the ingredients needed to shake up the Italian economy is an injection of managerial and entrepreneurial capabilities. For a definition of entrepreneurial capital, we can refer to Audretsch and Keilbach (2003, 2004): they suggest that entrepreneurship is related to change, driven by the ability to perceive new economic opportunities and subsequently introduce new ideas on the market. In a similar direction, in a EC - Green Paper (2003) on Entrepreneurship, the European Commission stated that it is the motivation and the ability of a single individual, alone or in an organisation, to recognise an economic opportunity and extract profit from it.

Returning to the works of Audretsch *et* al. (2003, 2004), they stated that entrepreneurship impacts on economic performance through three channels: the first involves the start-up and growth of new enterprises. In this way, the entrepreneur serves the role of gathering knowledge spillovers from their sources, transforming

[7] Here, the analysis has to be slightly more aggregated (two digits or 20 industries).

Table 4

ESTIMATED MARK-UPS AT INDUSTRY LEVEL IN ITALY (1981-2005)

Sector	NACE Code	Lerner Index	Std. Error	p-value	Mark -up ratio
Manufacturing					
Food, drink & tobacco	(15-16)	0.10	0.00	0.00	1.11
Textiles & textile products	(17-18)	0.12	0.01	0.00	1.13
Leather & footwear	(19)	0.14	0.01	0.00	1.16
Wood & products of wood & cork	(20)	0.13	0.01	0.00	1.15
Pulp, paper products, printing & publishing	(21-22)	0.15	0.01	0.00	1.17
Mineral oil refining, coke & nuclear fuel	(23)	0.10	0.02	0.00	1.11
Chemicals	(24)	0.14	0.01	0.00	1.17
Rubber & plastics	(25)	0.14	0.01	0.00	1.16
Non-metallic mineral products	(26)	0.19	0.01	0.00	1.23
Basic metals & fabricated metal products	(27-28)	0.12	0.01	0.00	1.14
Mechanical engineering	(29)	0.13	0.01	0.00	1.15
Electrical & optical equipment	(30-33)	0.15	0.01	0.00	1.18
Transport equipment	(34-35)	0.10	0.01	0.00	1.11
Manufacturing NEC	(36)	0.12	0.01	0.00	1.14
Utilities					
Electricity, gas & water supply	(40-41)	0.25	0.03	0.00	1.33
Services					
Wholesale & retail trade; repairs	(50-52)	0.20	0.01	0.00	1.25
Hotels & restaurants	(55)	0.08	0.02	0.00	1.09
Transport & storage & communication	(60-64)	0.19	0.02	0.00	1.23
Financial intermediation	(65-67)	0.22	0.04	0.00	1.29
Real estate, renting & business activities	(70-74)	0.56	0.01	0.00	2.25

them into economic products: a scientist or an employee of an established firm who has an innovative idea from a knowledge source may decide to start a new firm in order to receive a better return on his/her idea. The second channel is the introduction of new competitors and hence the increase in (beneficial) competitive pressures. The third is the enhancement of firms' diversity, allowing them to explore a wider space in «economic ideas», which is one of the most powerful mechanisms of innovation.

These abilities are self-reinforcing, in the sense that an environment rich in knowledge and conducive to business ideas represents a stock of entrepreneurial capital. A natural empirical counterpart of this concept is the number of start-up and new firms. Audretsch *et* al. (2003, 2004) analyse the development of start-ups in German regions relative to their population in order to gauge their propensity to start new firms.

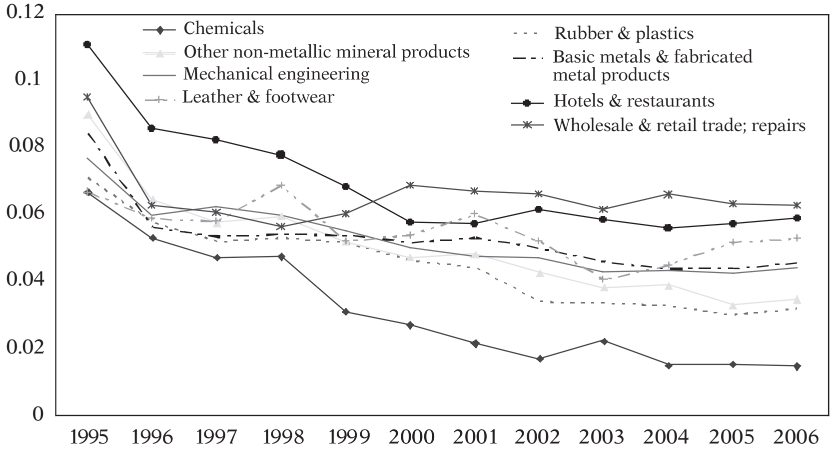
3.1 *A Possible Measure for Italian Sectors*

While the geographical content of this concept is clear and can be traced back to the analysis of particular regional concentrations, like Silicon Valley, Bangalore or districts in Italy, we did not believe that there was anything preventing an industrial interpretation: in fact, again considering Italy, there is much more than one district of shoemakers or mechanical instruments manufacturers, and they are spread over many regions; their interaction has probably increased recently and the kind of spillovers that characterise entrepreneurship activity are likely also at work on an industry basis, beyond geographical location. Hence, we use data from the database MOVIMPRESE (maintained by Italy's Chambers of Commerce, with available figures starting from 1995) on the number of new firms, the total number of active firms and those who have ceased activity, disaggregated by sector. Here (to compare data with national accounts figures), we use the same level of disaggregation (two digits) employed in the analysis of the estimated mark-up.

Graph 1 shows the ratio of newly registered firms to active companies for some sectors over the period 1995-2006. It reveals

GRAPH 1

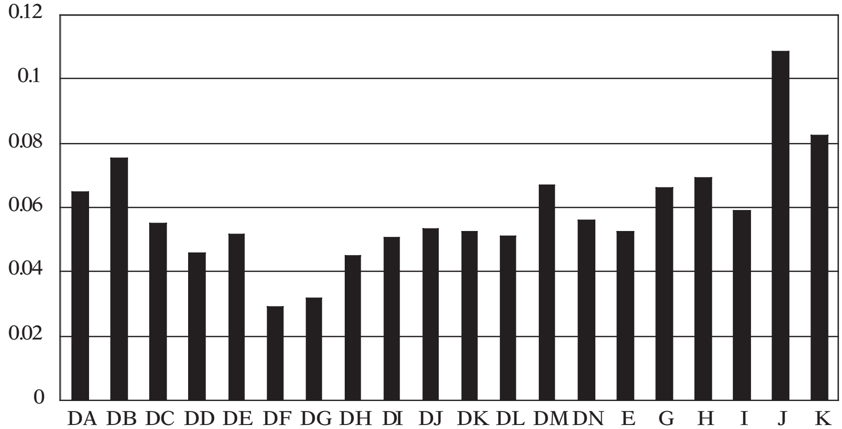
THE BIRTH RATE OF ITALIAN FIRMS ACROSS DIFFERENT SECTORS



the great heterogeneity among sectors, while Graph 2 shows the average business birth rate in the period.

GRAPH 2

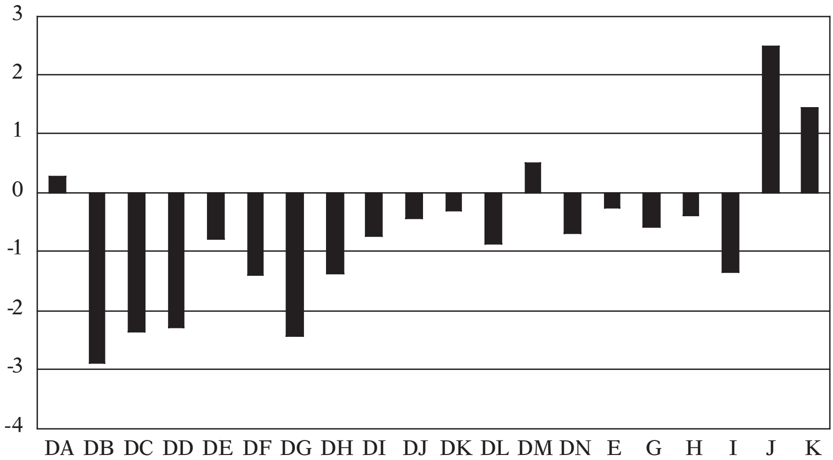
AVERAGE BUSINESS BIRTH RATE ACROSS DIFFERENT SECTORS IN THE PERIOD 1995-2006*



(*) The sector codes are reported in Table 11 in *APPENDIX A*.

Graph 3

AVERAGE RATIO (ENTRY-EXIT)/TOTAL ACTIVE FIRMS
IN THE PERIOD 1995-2006*
(in percent)



(*) The sector codes are reported in Table 11 in *APPENDIX A*.

Graph 3 illustrates the differences across sectors through another potentially relevant measure: the ratio of the entry-exit balance and total active firms (particularly useful to take into account the fact that some industries have a high birth rate but also a high mortality rate); in the following, we will refer to this measure as the birth balance.

3.2 *Modelling Entrepreneurial Capital in Italy*

As a first step, we followed the suggestion of Audretsch *et* al. (2003, 2004) to consider entrepreneurial capital as another factor of production along with the more usual factors. In a simple growth accounting framework, however, it is impossible to take into account entrepreneurial capital because of the impossibility of relating remuneration to this factor (just like total compensation for labour or gross operating profits).

Nonetheless, some positive correlation between calculated TFP[8] and business birth rates (or the ratio between the entry-exit balance and total active firms) is visible.[9]

Hence, the suggestion to consider entrepreneurial capital as another factor of production could help us to understand the mechanics of growth. In order to get further confirmation of this idea, we run a simple stochastic frontier analysis considering the figures of each industry as if they were different entities. Firstly, we estimate a simple Cobb-Douglas production function to confirm the share of the factors. We estimated the following equation:

$$\ln(Y_{it}) = \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + (v_{it} - u_{it}) \qquad (1)$$

where Y_{it} is real value added (VA) of sector i at time t, i=1,...,N and t t=1,...,T, K_{it} is the capital stock, L_{it} is the number of employed workers, and the error is modelled as a *i.i.d.* with zero mean and σ_v^2 variance (v_{it}) minus a truncated normal error intended to capture inefficiency (u_{it}).

The results of the estimation, which is kept as simple as possible with no variation in time imposed for inefficiency estimates, are shown in Table 5.[10] The coefficients are significant and of the expected signs. In terms of magnitude, they do not exceed the product, and their sum is less than 1 (see Table 5).

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[8] We have calculated TFP growth in Italian industries at two-digit level, resorting to a simple growth accounting exercise, whose results are reported in Table 11 in *APPENDIX A*. The data show a fairly steep decline in TFP in the last five years in almost all industries (the exceptions being Metals and fabricated metal products and Other non-metallic mineral products, Electricity, Transport and storage and Financial intermediation).

[9] This correlation is stronger for manufacturing than for services, but this result requires further investigation.

[10] In this Section, the estimation has been performed using Frontier 4.1 provided by Coelli on his website, see COELLI T.J. (1996). We indicate with β_0 the intercept, and with β_1 and β_2 the coefficient on capital and labour respectively, Sigma-squared represents the sum of the estimated variances of v and u, while Gamma is the ratio of the variance of u to Sigma-squared and hence represents the significance of the SFA estimation.

TABLE 5

A TRADITIONAL COBB-DOUGLAS ESTIMATION (1995-2005)

	Coeff	Std. Error	*t*-ratio
β_0	4.204	0.502	8.382
β_1	0.265	0.076	3.496
β_2	0.537	0.081	6.622
Sigma-squared	0.348	0.172	2.023
Gamma	0.981	0.010	97.250
mu is restricted to be zero			
eta is restricted to be zero			
Log-likelihood function		189.993	
LR test of the one-sided error		368.594	
with number of restriction		1	

Then, we ran the same analysis assuming that entrepreneurial capital is another factor of production. The results are shown in Table 6.[11]

Once again, coefficients are significant and of the expected signs; the proposed measures of entrepreneurial capital contributes positively to the output as a production factor, and are broadly equivalent in terms of significance. Obviously, there is a problem of endogeneity, but the results do not change particularly, considering lagged demographic variables or lagged moving averages.[12]

Hence, these preliminary results seem to confirm that there is a role for something that can be viewed as manageriability or entrepreneurial capital in explaining the output that a firm or in this case an industry, that is an aggregation of firms, can achieve. Nonetheless, we can easily accept that the role of an entrepreneur (if we think of a start-up) or management is to find the right combination of production factors, hence fostering their efficient usage. In this respect, it seems useful to directly consider entrepreneurial capital as a variable that helps to explain

[11] We indicate the entrepreneurial capital coefficient with β_3.

[12] Considering two years of leads or lags of the proposed measure does not alter the signs or the magnitude of the coefficients.

TABLE 6

THE ROLE OF ENTREPRENEURIAL CAPITAL

With birth rate	Coeff	Std. Error	*t*-ratio	With birth balance	Coeff	Std. Error	*t*-ratio
β_0	4.006	0.205	19.534	β_0	4.157	0.187	22.288
β_1	0.293	0.025	11.583	β_1	0.279	0.024	11.676
β_2	0.493	0.021	24.001	β_2	0.515	0.022	22.987
β_3	0.071	0.017	4.179	β_3	0.015	0.005	3.264
Sigma-squared	0.320	0.097	3.306	Sigma-squared	0.310	0.102	3.043
Gamma	0.981	0.006	157.821	Gamma	0.980	0.007	138.840
mu is restricted to be zero				mu is restricted to be zero			
eta is restricted to be zero				eta is restricted to be zero			
Log-likelihood function		197.740		Log-likelihood function			195.122
LR test of the one-sided error		383.847		LR test of the one-sided error			374.294
with number of restriction		1		with number of restriction			1

inefficiency. As shown in Battese and Coelli (1995), we can at the same time estimate:

$$\text{(2)} \qquad \ln(Y_{it}) = \beta_0 + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + (v_{it} - u_{it})$$
$$u_{it} = \delta_0 + \delta_1 du1 + \delta_2 du2 + \delta_3 du3 + \delta_4 (entrepr.capital) + \omega_{it}$$

where the dummies are constructed in order to group sectors that are non-ICT manufacturing sectors (*du*1), manufacturing using- or producing-ICT (*du*2), non-ICT service sectors (*du*3) and ICT-using and -producing services. If the deltas are negative, they subtract from inefficiency. With this specification, efficiency is evaluated for each period t, t=1,...,T, of the sample. Table 7 shows the results of this estimation. In this estimation we used the business birth balance measure. The coefficient on entrepreneurship is negative and significant: the higher the entrepreneurial capital, the lower the sector's inefficiency. The significance of the gamma coefficient validates the hypothesis on the structure of errors (*i.e.* the use of the SFA approach), and hence, of the proposed measure of entrepreneurial capital as an explanatory variable for efficiency. All the coefficients are highly significant (with the partial exception of the coefficient on the dummy for non-ICT service sectors, which is significant at the 10% confidence level).

Moreover, looking at the path of the estimated efficiency by industry, a notable heterogeneity emerges, although in general it seems that the distance from the efficient frontier is widening. Graph 4 shows the different path of some manufacturing industries, and highlights the stability in Wood and Basic metals and, in contrast, the substantial decline in the efficiency scores for Coke and refineries (not included in the Graph), Textiles, Leather and Pulp and paper products. However, almost all industries have been on a downtrend since 2000.

It may be instructive to compute the differences between efficiency scores (Eff.) at the beginning and end of the period (weighted by their level at the beginning) and compare the results with the average total factor productivity (Table 11 in the *Appendix A*) in the same period: there is in fact a clear and wide

TABLE 7

ENTREPRENEURIAL CAPITAL AND TECHNICAL EFFICIENCY

	Coeff	Std. Error	*t*-ratio
β_0	3.104	0.206	15.061
β_1	0.437	0.020	21.978
β_2	0.376	0.019	20.238
δ_0	-0.866	0.441	-1.963
δ_1	1.342	0.440	3.048
δ_2	1.299	0.445	2.920
δ_3	0.902	0.477	1.891
δ_4	-0.038	0.013	-2.992
Sigma-squared	0.039	0.004	9.859
Gamma	0.44	0.10	4.44
Log-likelihood function		55.74	
LR test of the one-sided error		90.78	
with number of restriction		6	

correlation between the two measures as Graph 5 clearly shows.[13] Nonetheless, Graph 5 also reveals that this correlation is much less strong for the Wholesale and retail trade (G) and Hotels and restaurant (H) sectors.

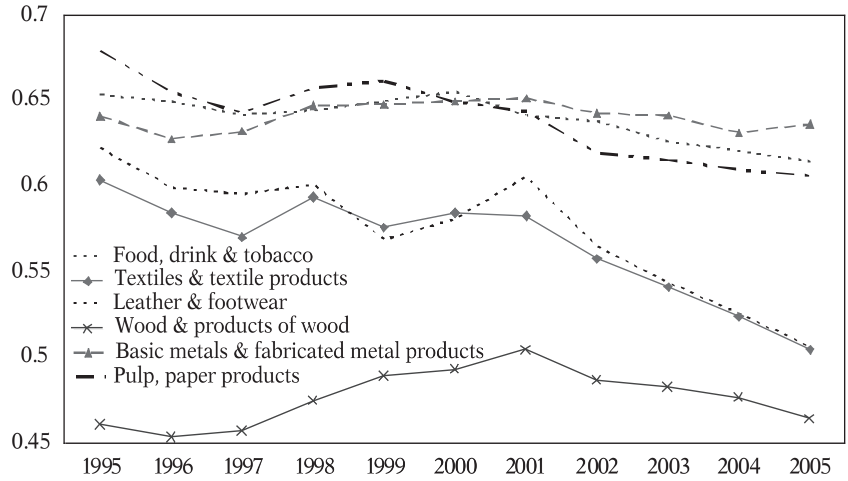
The proposed measure of entrepreneurial capital helps to explain the efficiency of different industries, and this efficiency is clearly related to the calculated TFP performance over the last few years; an immediate policy implication here is the need to foster an environment that is as conducive as possible to this entrepreneurial capital and, hence, to enhance initiatives intended to facilitate the creation of new firms and remove bureaucratic obstacles to entrepreneurial initiatives. These should on the one hand foster competition *per se*, and on the other, directly enhance the importance of a factor of production that seems to play a fairly significant role in explaining long-term performances.

As we said at the beginning of this Section, the measure we use for entrepreneurial capital must be considered more as an

[13] Downward oriented spikes refer to DB, DC, DE and DF, the industries mentioned above.

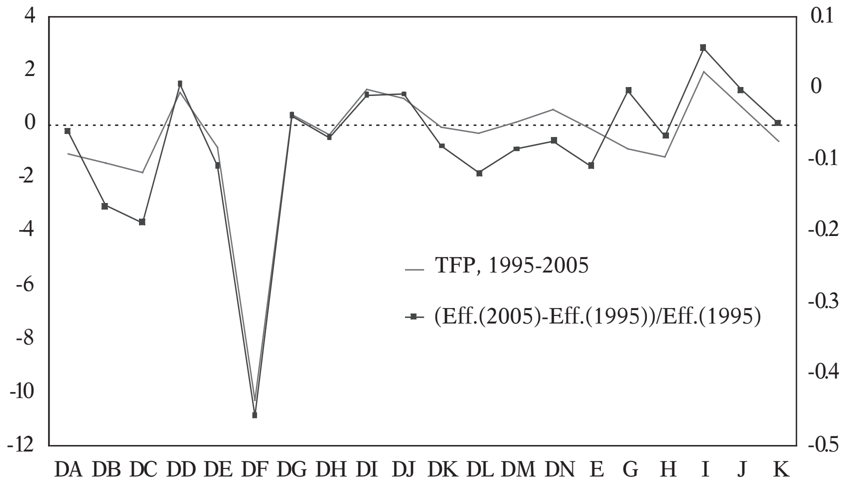
Graph 4

TECHNICAL EFFICIENCY ESTIMATES IN THE PERIOD 1995-2005



Graph 5

TECHNICAL EFFICIENCY ESTIMATES AND TFP IN THE PERIOD 1995-2005



index than a direct measure, which obviously is hard to gauge. Nonetheless, the analysis showed its potential relevance quite convincingly. Nevertheless, we want to pursue another route to measure entrepreneurship contribution, trying to extract it directly from data on production and the usual factors of production and considering it as an unobservable variable. This is the aim of the second part of the paper.

4. - Entrepreneurship as an Unobservable Factor

Until now, we have discussed the potential relevance of entrepreneurship capital to explain the differences in efficiency across sectors in Italy. In this Section, we pursue the same aim but, since we are aware of the difficulties of identifying a correct measure of entrepreneurship, we introduce managerial ability as an unobservable input. The direct consequence of this assumption is that we have to abandon the stochastic frontier model specification with constant parameters adopted so far, and introduce a random coefficient stochastic frontier model, in the same spirit as Tsionas (2002) and Alvarez, Arias and Greene (2004). In this new context, differences in the estimated technical efficiencies, with respect to a fixed coefficient SFA model, pick up differences in the level of managerial ability across industry sectors in Italy. In addition, a random coefficient stochastic frontier model allows for sector-specific efficiency to be separated from the technological heterogeneity across sectors.[14] The model's general form may be written as:

$$y_{it} = \alpha_i + x'_{it}\beta_i + v_{it} - u_{it} \tag{3}$$

where y_{it} is a single output endogenous variable for the sector i, i=1,...,N at time t, t=1,...,T, v_{it} is the sector and time-specific stochastic part of the frontier, with v_{it} ~ *i.i.d.* $N(0, \sigma^2)$ and u_{it} is a non-negative disturbance representing technical inefficiency, *i.e.*

[14] This may better capture what we observed before, *i.e.* different productivity performances characterising ICT-producing, ICT-using and non-ICT sectors.

TE_{it} = exp($-u_{it}$). Moreover, it is assumed that x_{it} is a (k x 1) vector of production inputs, β_i (k x 1) is a random regressor coefficients vector for i=1,...,N, while α_i for any i defines a cross-sectional random intercept[15]; we assume that all β_i and α_i are independent, and the errors v_{it} and u_{it} are independent of x_{it}.

As in Tsionas (2002), this stochastic frontier specification means that in the first stage, each sector owns a specific set of technological coefficients β_i, which enables different production possibilities among sectors to be defined. In the second stage, each sector experiences a shock that determines its inefficiency level u_{it}, through a single parameter θ exponential distribution. However, unlike Tsionas' specification, we assume that the model intercept is also random,[16] and this assumption allows us to relate sector-specific technical efficiency more directly to potential sector managerial ability (see Alvarez, Arias and Greene, 2004). Let us provide an example of this analytical linkage. In detail, given a managerial ability unobservable input m_i, we indicate with m_i^* the level of the management that defines the frontier of each sector i, for i=1,..., N; it is possible to relate to technical efficiency and managerial ability by observing that the sector's efficient output y_{it}^* can be now defined as:

$$(4) \qquad \begin{aligned} y_{it}^* &= \mu + x'_{it}\beta_i + \beta_m m_i^* + v_{it} \\ y_{it} = y_{it}^* - u_{it} &= (\mu + \beta_m m_i^*) + x'_{it}\beta_i + v_{it} - u_{it} \end{aligned}$$

where μ indicates a fixed intercept in the model; then, by simply redefining $\alpha_i = \mu + \beta_m m_i^*$, for i=1,..., N, we come back to the general model:

$$y_{it} = \alpha_i + x'_{it}\beta_i + v_{it} - u_{it}$$

which has the appearance of the random coefficient stochastic frontier model introduced in *(3)*. We conclude that in our final

[15] The input and the output variables in the model are, conventionally, expressed in logs, with y_{it} = ln(Y_{it}) and x_{it} = ln(X_{it}).

[16] By taking advantage of the panel nature of our dataset, we may bypass the potential identification problem between the random intercept term and the idiosyncratic measurement error affecting cross-section data.

model specification, entrepreneurship is introduced as an unobservable variable that can be seen and estimated as a random intercept in a stochastic frontier model with random slope coefficients, which allow us to better distinguish between technological differences and technology-specific inefficiencies[17] related to different levels of managerial ability.

To complete the specification of the model in *(3)*, we introduce the probability distributions for all model random coefficients as:

$$\alpha_i \sim N\left(\bar{\alpha}, \sigma_\alpha^2\right) \qquad (5)$$
$$\beta_i \sim N_k\left(\bar{\beta}, \Omega\right)$$

with $\bar{\alpha}$ and $\bar{\beta}$ representing, respectively, a scalar and a (k x 1) vector of parameter means, and Ω defining a positive definite (k x k) variance-covariance matrix.

For inference in the model in *(3)*, we make use of Bayesian methods,[18] by defining a Gibbs sampling algorithm with data augmentation (Chib and Greenberg, 1995), which is useful to simulate the marginal posterior distribution of all model parameters (σ^2, σ_a^2, Ω, $\bar{\alpha}$, $\bar{\beta}$, θ) and the unobserved variables (α_1,..., α_N, β_1',..., β_N', u_1',..., u_N'). This method allows us to efficiently estimate all unobservable variables in the model, also computing their complete probability distributions, and not only the point estimates.

As we know, the implementation of the Bayesian analysis requires us to assign a probability distribution not only to the observable data but also to the model parameters, and in our analysis we adopt proper conjugate prior distributions to capture the non-sample information on the parameters, supposing that all the elements of the parameter vector are independent.

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[17] Unlike ALVAREZ A. - ARIAS C. - GREENE W. (2004), we adopt a specification in which inputs enter the model linearly, and not through a translog production function. This implies that, in this first step of the analysis, we do not fully consider the direct interaction of the management unobservable variable with the remaining productive inputs (capital and labour). We are conscious that by adopting this linear specification some potential identification problems could emerge.

[18] Details on MCMC simulation methods and their applications in Bayesian time-varying parameter models are available in FEDERICO L. (2004), and the references therein, available on request.

In the analysis, the parameter σ^2 is a normal variance, therefore the conjugate prior distribution for its precision $h = \sigma^2$ will be a Gamma distribution with shape parameter v_0 and scale h_0. Moreover, given the high dimension of the parameter space, we introduce hierarchical priors and we treat $\bar{\alpha}$, $\bar{\beta}$, σ_a^{-2}, Ω as unknown further parameters that require their own prior. In particular, we adopt non-informative Normal priors for the hyperparameters $\bar{\alpha}$ and $\bar{\beta}$, respectively of the form $N(\bar{\alpha}_{0a}, \sigma_a^2)$ N_k $(\bar{\beta}_{0\beta}, \Omega_\beta)$, so all information resulting in their posterior distribution arises from the data. We use a k-dimensional Wishart as a prior distribution for the precision matrix $H = \Omega^{-1}$, $H \sim W_k(m_0, M^{-1}{}_0)$ and $m_0>0$, and we assume that $h_\alpha = \sigma_a^{-2}$ admits a prior Gamma distribution of the form, $h_\alpha \sim G(v_{0,\alpha}, h_{0,\alpha})$. Finally, we employ a prior for the parameter θ of the inefficiency exponential distribution, which is still a Gamma distribution of the form: $\theta \sim G(v_{0,\theta}, \theta_{0,\theta})$.

We discuss the determination of the full conditional posterior distributions for our stochastic frontier model with random coefficients in *Appendix* B. For parameter estimation, we run the Gibbs sampler with 12,000 iterations; the first 2,000 are discarded in the initial transient (burn-in) phase, in which the Gibbs sampling algorithm reaches convergence, and the next 10,000 are recorded and used to compute moments of the posterior distributions.[19] We face major difficulties in the convergence of the algorithm for the random coefficient model, with respect to an SFA model with non-random parameters, given the greater complexity of the model and given our choice of adopting a non-informative prior also for the parameter of the exponential distribution of the inefficiency.[20]

As in the previous Section, in this empirical application we use data from a balanced panel of the twenty Italian sectors. However, in this Section we can take advantage of the longer series available for the real value added, employment and stock of capital

[19] The random coefficient stochastic frontier model is estimated using MATLAB software produced by the authors.

[20] Information about the performance of the Gibbs sampling algorithm is available on request. For a review, see GEWEKE J. (1992).

(ignoring the business birth rates), and we have observations for the period between 1981-2005. As for the choice of priors' hyperparameters, we assume a relatively non-informative prior for the median efficiency, with $v_{0,\theta}$=2 and $\theta^{-1}{}_{0,\theta}$=-ln(0.50), whole for the remaining constant parameters, we specify a non-informative prior of the form: v_0=1 and $h^{-1}{}_0=10^{-3}$, m_0=3, $M_0=3.3^{-7}$ and $v_{0,\alpha}$=1, $h^{-1}{}_{0,\alpha}=10^{-4}$.

Table 8 summarises the inference on the posterior distributions of all parameters of the model in *(3)*, reporting posterior means, posterior standard deviations (henceforth S.D.) and the 95 percent interval of any posterior distribution.[21] Table 8 also shows the estimated parameters of fixed coefficient stochastic frontier models, respectively with time-variant and time-invariant technical efficiency (TE).

Posterior means of the parameters differ across the three models, especially for estimates of the parameter variance and the parameter θ, as the alternative specifications tend to cause different shifts in the variation between the inefficiency term and the symmetric idiosyncratic error. Moreover, the possibility of accounting for the differences of managerial abilities across sectors, through a random coefficient specification for the stochastic frontier, modifies the posterior mean estimate of θ, which is the crucial parameter of the distribution of the inefficiency. In particular, for the random coefficient model, we get the lower posterior estimates of this parameter (θ is around 0.17), which implies values of the efficiency (exp($-u_{it}$)), averaged across time, ranging from 0.64 to 0.94. For the fixed coefficient SFA with time-variant technical efficiency, the estimated posterior mean of θ is greater than 0.18, which entails lower values for the technical efficiencies. This result tends to confirm that accounting for the potential effect of management on production may correct some Italian sectors' measures of technical inefficiency, which could be otherwise wrongly inflated. These differences are

[21] We indicate with α the intercept term and with β_1 and β_2 the coefficients of capital and labour respectively; Precision (h) represents the inverse of the equation variance and Teta the parameter of the inefficiency exponential distribution.

Table 8

POSTERIOR DISTRIBUTIONS OF THE PARAMETERS FOR RANDOM* AND FIXED COEFFICIENT STOCHASTIC FRONTIERS

	Posterior distribution			
	Mean	S.D.	Lower	Upper
Random coefficient time-variant TE				
α	0.616	0.217	0.347	1.135
β_1	0.542	0.026	0.480	0.570
β_2	0.539	0.020	0.517	0.588
Precision (h)	90.63	16.875	62.79	128.3
Teta	0.165	0.029	0.104	0.220
Fixed coefficient time-variant TE				
α	0.836	0.005	0.824	0.845
β_1	0.506	0.003	0.500	0.512
β_2	0.572	0.005	0.561	0.583
Precision (h)	79.675	15.155	54.95	114.57
Teta	0.183	0.015	0.155	0.212
Fixed coefficient time-invariant TE				
α	2.348	0.339	1.692	2.997
β_1	0.594	0.020	0.553	0.633
β_2	0.260	0.031	0.200	0.320
Precision (h)	114.4	7.615	100.1	129.8
Teta	0.807	0.204	0.492	1.294

(*) For the random coefficients model, the estimated coefficients are parameter means.

amplified when we compare the random coefficient model with a non-random coefficient model in which the technical efficiency is a priori assumed to be time-invariant.

In Table 9, we show the values of the average technical efficiency for every Italian industry sector over the period 1981-2005, according to the random coefficient model with time-variant TE and the two fixed coefficient models. From the models of the Table, the most efficient sectors appear to be Wholesale and retail trade, Hotels and restaurant, followed by Electrical and optical equipment, according to the random coefficient model. The most inefficient sectors are Wood and products of wood, Basic metals and fabricated metal products, Real estate, renting and business activities, Textile and textile products and Transport equipment.

TABLE 9

ESTIMATED TECHNICAL EFFICIENCY
IN ITALIAN INDUSTRY SECTORS

Sector	Random coefficient time-variant TE	Fixed coefficient time-variant TE	Fixed coefficient time-invariant TE
Manufacturing			
Food, drink & tobacco	0.890 (9)	0.879 (9)	0.483 (9)
Textiles & textile products	0.767 (16)	0.713 (18)	0.437 (11)
Leather & footwear	0.922 (6)	0.908 (7)	0.497 (8)
Wood & products of wood & cork	0.638 (19)	0.592 (19)	0.255 (19)
Pulp, paper products, printing & publishing	0.930 (4)	0.929 (5)	0.501 (7)
Chemicals	0.852 (13)	0.848 (12)	0.376 (16)
Rubber & plastics	0.865 (11)	0.850 (10)	0.362 (18)
Non-metallic mineral products	0.870 (10)	0.850 (11)	0.410 (14)
Basic metals & fabricated metal products	0.756 (18)	0.718 (17)	0.419 (12)
Mechanical engineering	0.899 (8)	0.891 (8)	0.517 (6)
Electrical & optical equipment	0.930 (3)	0.926 (6)	0.583 (3)
Transport equipment	0.810 (15)	0.782 (15)	0.376 (17)
Manufacturing NEC	0.861(12)	0.832 (13)	0.418 (13)
Utilities			
Electricity, gas & water supply	0.928 (5)	0.944 (1)	0.390 (15)
Services			
Wholesale & retail trade; repairs	0.936 (1)	0.935 (2)	0.961(1)
Hotels & restaurants	0.935 (2)	0.934 (3)	0.699 (2)
Transport & storage & communication	0.840 (14)	0.824 (14)	0.522 (5)
Financial intermediation	0.922 (7)	0.930 (4)	0.541 (4)
Real estate, renting & business activities	0.767 (17)	0.774 (16)	0.441 (10)

Table 10

ESTIMATED TECHNICAL EFFICIENCY OVER TIME

	Random coefficient time-variant TE	
	Mean	S.D.
1981	0.833	0.134
1982	0.825	0.131
1983	0.824	0.122
1984	0.836	0.113
1985	0.841	0.106
1986	0.843	0.107
1987	0.849	0.104
1988	0.860	0.097
1989	0.865	0.092
1990	0.863	0.089
1991	0.856	0.086
1992	0.855	0.086
1993	0.849	0.094
1994	0.871	0.082
1995	0.881	0.077
1996	0.877	0.078
1997	0.881	0.073
1998	0.879	0.071
1999	0.879	0.069
2000	0.885	0.066
2001	0.880	0.067
2002	0.871	0.073
2003	0.859	0.076
2004	0.861	0.082
2005	0.852	0.093

Table 10 shows average technical efficiencies *per annum* for all Italian industry sectors according to the random coefficient stochastic frontier model. Following the results of Table 10, the average technical efficiency in this model varies between 82% and 89%, and, in line with the results of the previous Section, the efficiencies are not stable over time. In particular, we discover that average efficiency has fallen significantly since 2000.

5 - Conclusions

A lot of different causes have been blamed for Italy's disappointing productivity and overall economic performance in the decade 1995-2005, including its specialisation in traditional goods, the excessively small size of its firms, and the decline in formalised research and development. Moving from aggregate figures to industry figures suggests that there is a huge deficiency in competitive pressures and market incentives to adopt best practice. This leads us to an examination of certain measures of entrepreneurship and entrepreneurial capital, to see if their trends could help to explain this disappointing performance or the related causes. Using a measure proposed (in a more geographical approach) by Audretsch and Keilbach (2003, 2004), we assess its relevance empirically, which also shows the great similarity between an efficiency score calculated starting from that measure and the total factor productivity (and also mark-up analysis) for different industries. Moreover, we also try to extract from data a measure of managerial ability, considering it as an unobservable and recurring to Bayesian techniques in order to perform the estimation, further reinforcing these observations. This suggests approaching entrepreneurial capital as a primitive issue, in a hierarchical approach: an industry that is rich in managerial ability will choose a more appropriate production technique and will draw near to the efficiency frontier; an economy that is rich in entrepreneurial capital will find the right incentives to establish itself in a proper position in export and production specialisation. An immediate policy implication here is the need to foster an environment that is as conducive as possible to this entrepreneurial capital and, hence, to enhance initiatives intended to facilitate the creation of new firms and remove bureaucratic obstacles to entrepreneurial initiatives. These should on the one hand foster competition *per se*, and, on the other, directly enhance the importance of a factor of production that seems to play a fairly significant role in explaining long-term performances.

APPENDIX A

The TFP Across Italian Industry Sectors

TABLE 11

TOTAL FACTOR PRODUCTIVITY AT INDUSTRY LEVEL IN ITALY (1992-2005)

Sector	NACE Code	1992-1995	1996-2000	2001-2005
Food, drink & tobacco	DA - (15-16)	0.8	0.0	-2.0
Textiles & textile products	DB - (17-18)	4.1	0.4	-4.2
Leather & footwear	DC - (19)	5.1	-1.6	-3.3
Wood & products of wood & cork	DD - (20)	1.6	3.9	-1.3
Pulp, paper products, printing & publishing	DE - (21-22)	2.4	-0.1	-1.5
Mineral oil refining, coke & nuclear fuel	DF - (23)	2.6	-15.6	-8.2
Chemicals	DG - (24)	4.5	0.7	-0.1
Rubber & plastics	DH - (25)	3.5	0.0	-0.6
Other non-metallic mineral products	DI - (26)	2.1	1.9	0.2
Basic metals & fabricated metal products	DJ - (27-28)	5.4	0.3	0.2
Mechanical engineering	DK - (29)	3.7	-0.9	-1.3
Electrical & optical equipment	DL - (30-33)	2.2	0.2	-1.9
Transport equipment	DM - (34-35)	2.0	1.9	-3.8
Manufacturing NEC	DN - (36)	3.7	0.4	-0.7
Electricity, gas & water supply	E - (40-41)	-0.7	-1.5	1.0
Wholesale & retail trade; repairs	G - (50-52)	1.8	-0.5	-2.3
Hotels & restaurants	H - (55)	1.6	0.8	-4.0
Transport & storage & communication	I - (60-64)	4.1	1.4	2.0
Financial intermediation	J - (65-74)	0.5	2.3	0.2
Real estate, renting & business activities	K - (70-74)	-1.0	-0.7	-0.9

APPENDIX B

The Gibbs Sampling Scheme

We report the Gibbs sampling scheme used to make inferences on the model in *(3)*, and discuss the determination of the full conditional distributions of all parameters in the model. Note that, notwithstanding the complexity of our model, the Gibbs sampling allows us to split the inferential problem into a series of simpler problems, which can be approached by using known Bayesian inference results.

Conditional posterior distribution of β_i

We write the regression model as:

$$y_{it} + u_{it} = \alpha_i + x'_{it}\beta_i + v_{it} \tag{6}$$

where the error terms are independent and identically distributed normal variables, $i=1,\dots,N$, $t=1,\dots,T$, $v_{it} \sim i.i.d.N(0, \sigma^2)$. The prior distribution for any β_i is the multivariate normal distribution in *(5)*. Depending on the observable data and remaining parameters, we can deduce that, for any sector i, $i=1,\dots,N$, the full conditional posterior distribution of β_i is a multivariate normal distribution of the form:

$$\beta_i \left| \sigma^2, \alpha_i, \sigma_\alpha^2, \Omega, \bar{\alpha}, \bar{\beta}, \theta, u, y, X \sim N_k\left(\beta^*, \Omega^*\right)\right. \tag{7}$$

where

$$\Omega^{*-1} = \left(\frac{\sum_{t=1}^{T} x_{it}x_{it}'}{\sigma^2} + \Omega^{-1} \right),$$

$$\beta_i^* = \left(\frac{\sum_{t=1}^{T} x_{it}x_{it}'}{\sigma^2} + \Omega^{-1} \right)^{-1} \left(\frac{\sum_{t=1}^{T} x_{it}\left(y_{it} + u_{it} - \alpha_i\right)}{\sigma^2} + \Omega^{-1}\bar{\beta} \right)$$

Conditional posterior distribution of α_i

At this point, we can consider β_i, for i=1,…,N as a set of known data, such as the endogenous and explanatory variables y_{it} and x_{it}. Then, by reconsidering the linear regression model in *(6)*, with disturbances distributed according to a normal distribution, and stated a Normal prior for α_i, equal to $\alpha_i \sim N(\bar{\alpha}, \sigma_\alpha)$, we derive the full conditional posterior distribution for α_i, i=1,…,N which is equal to:

$$\alpha_i \left| \beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \bar{\alpha}, \bar{\beta}, \theta, u, y, X \sim N\left(\alpha^*, \sigma^{*2}\right)\right. \tag{8}$$

where

$$\sigma^{*-2} = \left(\frac{T}{\sigma^2} + \sigma_\alpha^{-2}\right), \alpha^* = \left(\frac{T}{\sigma^2} + \sigma_\alpha^{-2}\right)^{-1} \left(\frac{\sum_{t=1}^{T}\left(y_{it} + u_{it} - x'_{it}\beta_i\right)}{\sigma^2} + \bar{\alpha}\sigma_\alpha^{-2}\right)$$

Conditional posterior distribution of σ^2

Let's take again the regression model as stated in *(6)*. By combining the normal likelihood of this model with a prior $G(v_0,h_0)$, we deduce that the full conditional posterior distribution of the constant parameter h=σ^{-2} is still a Gamma distribution of the form:

$$h \left| \beta_i, \sigma_\alpha^2, \Omega, \alpha_i, \bar{\alpha}, \bar{\beta}, \theta, u, y, X \sim G\left(v_1, h_1\right)\right. \tag{9}$$

where the posterior parameters are v_1 = NT + v_0 and:

$$h_1^{-1} = \left(\frac{\sum_{t=1}^{T}\sum_{i=1}^{N}\left(y_{it} + u_{it} - \alpha_i - x_{it}'\beta_i\right)^2}{2} + h_0^{-1}\right)$$

Conditional posterior distribution of $\bar{\beta}$

By treating the generated random coefficients β_i, for i=1,…,N, as a set of known data and by adopting a normal non-informative prior for $\bar{\beta}$ of the form $N_k(\bar{\beta}_{0\beta}, \Omega_\beta)$ we deduce that the conditional posterior distribution of $\bar{\beta}$ is a Normal distribution of the form:

$$\bar{\beta}\left|\beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \alpha_i, \bar{\alpha}, \theta, u, y, X \sim N\left(\beta_1, \Omega_1\right)\right. \tag{10}$$

where

$$\Omega_1^{-1} = \left(\Omega^{-1}{}_\beta + \Omega^{-1} N\right), \bar{\beta}_1 = \left(\Omega^{-1}{}_\beta + \Omega^{-1} N\right)^{-1} \left(\Omega^{-1}{}_\beta \bar{\beta}_{0\beta} + \Omega^{-1} \sum_{i=1}^N \beta_i\right)$$

Conditional posterior distribution of $\bar{\alpha}$

In a similar way, given the known random intercepts α_i, $i=1,\ldots,N$, and a Normal prior for $\bar{\alpha}$, $N(\bar{\alpha}_{0\alpha}, \sigma^2_{0\alpha})$, it is easy to show that $\bar{\alpha}$ admits a conditional posterior distribution of the form:

$$\bar{\alpha}\left|\beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \alpha_i, \bar{\beta}, \theta, u, y, X \sim N\left(\bar{\alpha}_{1\alpha}, \sigma^2_{1\alpha}\right)\right. \tag{11}$$

with posterior moments determined by:

$$\sigma_{1\alpha}{}^{-2} = \left(\sigma_{0\alpha}^{-2} + \sigma_\alpha^{-2} N\right), \bar{\alpha}_{1\alpha} = \left(\sigma_{0\alpha}^{-2} + \sigma_\alpha^{-2} N\right)^{-1} \left(\sigma_{0\alpha}^{-2} \bar{\alpha}_{0\alpha} + \sigma_\alpha^{-2} \sum_{i=1}^N \alpha_i\right)$$

Conditional posterior distribution of Ω

Once the latent variables β_i, $i=1,\ldots,N$ have been determined, and a prior Wishart has been defined for the dispersion matrix $H = \Omega^{-1}$ of the form $W_k(m_0, M^{-1}{}_0)$, we can get the kernel of the conditional posterior distribution of H as:

$$p\left(H\left|\beta_i, \sigma^2, \sigma_\alpha^2, \bar{\alpha}, \alpha_i, \bar{\beta}, \theta, u, y, X\right.\right) \propto |H|^{(N+m_0-k-1)/2}$$

$$\exp\left\{-\frac{1}{2} tr\left[\sum_{i=1}^N (\beta_i - \bar{\beta})(\beta_i - \bar{\beta})' + M^{-1}{}_0\right] H\right\}$$

Then, the full conditional posterior distribution of $\Omega^{-1} = \mathrm{H}$ reproduces the form of its prior distribution:

$$\Omega^{-1}\Big|\beta_i,\sigma^2,\sigma^2_\alpha,\bar{\alpha},\alpha_i,\bar{\beta},\theta,u,y,X \sim W(m_1,M_1^{-1}),$$

(12)

$$m_1 = N + m_0, M_1 = \left[\sum_{i=1}^{N}(\beta_i - \bar{\beta})(\beta_i - \bar{\beta})' + M^{-1}{}_0\right]^{-1}$$

Conditional posterior distribution of σ^2_α

In a similar way, given the vector of latent intercepts α_i for i=1,...,N and given a prior for $h_\alpha = \sigma^{-2}_\alpha$ which is a Gamma $G(v_{0,\alpha}, h_{0,\alpha})$, we can derive the full conditional posterior distribution of h_α which is still a Gamma distribution of the form:

$$\sigma^{-2}_\alpha\Big|\beta_i,\sigma^2,\Omega,\bar{\alpha},\alpha_i,\bar{\beta},\theta,u,y,X \sim \mathrm{G}(v_{1,\alpha},h_{1,\alpha}),$$

(13)

$$v_{1,\alpha} = N + v_{0,\alpha}, h^{-1}_{1,\alpha} = \left(\frac{\sum_{i=1}^{N}\left(\alpha_i - \bar{\alpha}\right)^2}{2} + h^{-1}_{0,\alpha}\right)$$

Finally, given all model parameters (σ^2, $\bar{\beta}$, $\bar{\alpha}$, Ω,σ^2_α) and the latent variable α_i and β_i, for any component i=1,...,N, the full conditional posterior distributions of the technical inefficiencies u_{it}, for i=1,...,N and t=1,...,T, based on the exponential distribution, can be stated as:

$$(14)\quad u_{it}\Big|\alpha_i,\beta_i,\sigma^2,\sigma^2_\alpha,\Omega,\bar{\alpha},\bar{\beta},\theta,y,X \sim N_{>0}(\alpha_i + x'_{it}\beta_i - y_{it} - (\theta h)^{-1}, h^{-1})$$

It follows that, given a prior gamma for θ of the form $G(v_{0,\theta}, \theta_{0,\theta})$, its full conditional posterior distribution will still be a Gamma $G(v_{1,\theta}, \theta_{1,\theta})$, with posterior moments defined as:

$$v_{1,\theta} = 2TN + v_{0,\theta}, \theta_{1,\theta} = \left(\sum_{t=1}^{T}\sum_{i=1}^{N}\left(u_{it}\right) + \theta^{-1}_{0,\theta}\right)^{-1}$$

Then, the Gibbs sampling for the stochastic frontier model with random coefficients defined in *(3)*, for any sector i, i=1,...,N at time t, t=1,...,T, is implemented by sampling $\beta_i^{(j)}$, $\alpha_i^{(j)}$, $\sigma^{2(j)}$, $\bar{\beta}^{(j)}$,

$\overline{\alpha}^{(j)}$, $\Omega^{(j)}$, $\sigma_\alpha^{2(j)}$, $u_{it}{}^{(j)}$, $\theta^{(j)}$, with j indicating the *j-th* iteration, j=1,…,M, from the chain:

$$\begin{gathered}
\beta_i^{(j)} \sim \beta_i \left| \sigma^2, \alpha_i, \sigma_\alpha^2, \Omega, \overline{\alpha}, \overline{\beta}, \theta, u, y, X \right. \\
\alpha_i^{(j)} \sim \alpha_i \left| \beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \overline{\alpha}, \overline{\beta}, \theta, u, y, X \right. \\
\sigma^{-2(j)} \sim \sigma^{-2} \left| \beta_i, \alpha_i, \sigma_\alpha^2, \Omega, \overline{\alpha}, \overline{\beta}, \theta, u, y, X \right. \\
\overline{\beta}^{(j)} \sim \overline{\beta} \left| \beta_i, \alpha_i, \sigma^2, \sigma_\alpha^2, \Omega, \overline{\alpha}, \theta, u, y, X \right. \\
\overline{\alpha}^{(j)} \sim \overline{\alpha} \left| \alpha_i, \beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \overline{\beta}, \theta, u, y, X \right. \\
\Omega^{-1(j)} \sim \Omega^{-1} \left| \alpha_i, \beta_i, \sigma^2, \sigma_\alpha^2, \overline{\alpha}, \overline{\beta}, \theta, u, y, X \right. \\
\sigma_\alpha{}^{-2(j)} \sim \sigma^{-2}{}_\alpha \left| \alpha_i, \beta_i, \sigma^2, \Omega, \overline{\alpha}, \overline{\beta}, \theta, u, y, X \right. \\
u_{it}^{(j)} \sim u_{\mathrm{it}} \left| \alpha_i, \beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \overline{\alpha}, \overline{\beta}, \theta, y, X \right. \\
\theta^{(j)} \sim \theta \left| \alpha_i, \beta_i, \sigma^2, \sigma_\alpha^2, \Omega, \overline{\alpha}, \overline{\beta}, u, y, X \right.
\end{gathered}$$

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