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**Productivity, Profitability and Financial Fragility:
Empirical Evidence from Italian Business Firms**

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Abstract

In this work we investigate two crucial dimensions of firms' structure and dynamics, that is profitability and productivity performance. The empirical distributions and the associated persistence over time are explored through a set of parametric and non parametric exercises performed on an large panel of Italian firms active in both Manufacturing and Services during the period 1998-2003. The main contribution resides in the use of an index of financial risk which allows us to document that not obvious interactions are in place among economic performances, financial conditions and availability of external credit. We also offer an initial understanding about how profitability and productivity relate with a third dimension of performance, that is firm growth. We find that, independently from the particular sector of activity and from financial conditions, there seems to be little market pressure and little behavioral inclination for the more efficient and more profitable firms to grow faster.

JEL codes: C14, D21, D24, L25, G30

Keywords: firm performance, profitability, productivity, financial constraints.

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1 Introduction

Firms' success stems from the many and complex interactions occurring among a number of firms' characteristics and choices. Pricing and marketing strategies, innovative activity, organizational structure, investment policy, all affect firms' performance. In this work, studying a large sample of Italian firms operating in both the manufacturing and service sectors, we mainly focus on two crucial dimensions of firms' activity: the ability to generate profits, and the efficiency through which production is carried on. Of course, these are among the topics that have received a long lasting attention within the evolution of economic theory. Similarly, applied work addressing issues such as, for instance, the contribution of inputs to output, firms' productivity, or the generation of economic value, is not certainly missing from the scene, especially in recent years, when the increasing availability of large longitudinal datasets has boosted the application of new and more sophisticated statistical techniques.

The main contribution pursued by the present analysis concerns the attempt to explore the relationships between firms' industrial performances and their financial conditions. This is done using an extensive source of accounting data collected and organized by *Centrale dei Bilanci* (CEBI, the Italian member of the European Committee of Central of Balance Sheet Data Office), who, since its foundation in the early '80s, has developed an internal rating procedure of the business companies covered by its database in terms of their expected ability to pay back the loans they received or, alternatively, to default. This results in assigning to each firm, for each year, an index of financial risk that we use in a relatively simple way: we group the firms in classes that, according to the rating, are likely experiencing similar financial condition, and we run a series of comparative analyses of the structure and the economic performances of firms belonging to the different classes.¹ Bottazzi *et al.* (2006) exploited this information in a similar way, studying firms' size and growth dynamics. The present work can be viewed as an attempt to enlarge the scope of that analysis to a wider representation of firms' activities, by interacting financial fragility with other dimensions of firms' operation. Profitability and production, we believe, are two crucial ones that are worth a further characterization. Indeed, while growth and market shares dynamics capture important pieces of revealed performance, firms' ability to earn profits play the role of a necessary condition to sustained growth, as profits represent not only the most obvious internal source of growth financing, but also help in raising external funds, as it is very likely that profitability is one of the main element that capital markets take into account when deciding where to allocate credit. But, then, one has to understand which are the conditions allowing a firm to represent a profitable economic activity. Simplifying to the extreme, basic economic reasoning would answer that, *coeteris paribus*, a firm must be able to set sufficiently high prices and, at the same time, to operate at sufficiently low costs. Then, the scope of manoeuvring would largely depend on how and how properly firms are able to organize production. Under this respect, a discussion of firms' productive structure and efficiency seems a natural step further necessary to account for a reasonably complete, though admittedly simplified, description of firms' dynamics.

Certainly, representing the overall financial condition of a firm by means of a single index entails an approximation which is, to a certain extent, questionable. The major drawback probably concerns the fact that the methodology used to build the rating index has not been disclosed to us. Though, we believe, it presents also two major advantages. First, it allows for a

¹The data have been made available to us by Unicredit Bank Research Office under the mandatory condition of censorship of any individual information.

synthetic and homogeneous assessment of firms' financial situation. A multivariate description considering several different aspects such, for instance, the relation between debt and cash flow, the structure of the former and its relationship with the ability of self-financing, and so on and so forth, although probably more complete, would have required a much more complicated analysis, inevitably entailing a greater number of arbitrary choices in terms of both methods and variables used. More importantly, limiting the attention to the rating index is appealing in that it is the kind of measure which, at least in first approximation, banks and other credit institutions look at when asked to provide the external capital necessary for the firm to run and expand. After all, CEBI itself build the index on the very behalf of the merchant banks who are among its major shareholders. In this respect, the index can also be considered a useful proxy for how, and to what extent, the economic performances of a firm affect (and are affected by) the ability to expand the available credit base and, indirectly, the costs payed by the firm to attain this expansion.

Note that the three dimensions of firms' activity we focus on, namely growth, profitability and productivity, are characterized by a decreasing distance from the ultimate definition of the financial capacity of a business firm and, consequently, should have an increasing impact on its financial health. It is then natural to expect that when we move from size, to profitability and, finally, to productivity dynamics the differences among the different risk classes will increase. As we will see below, this is, to a large extent, true. However, sometimes it is true in a rather unexpected way.

The structure of the work is as follows. In Section 2 we present a short description of the dataset we had access to, discussing, in particular, the choices we made to clean the sample. Section 3 presents a series of parametric and non-parametric statistical analyses of firms profits and profitability distributions and dynamics, comparing results across sector of activity and risk classes. Similar analyses are performed in Section 4, where, after discussing the degree of heterogeneity in the amount of inputs (labour and capital) used and their contribution to the output of different firms, we study the empirical distribution and the autoregressive structure of firms' productivity. Finally, in Section 5, we explore the relationships between firms' growth, profitability and productivity. This recomposes the picture about firms' performance and concludes.

2 Data Description

The data come from the CEBI database, which is one of the richest sources of information about balance sheet data for Italian firms. The original sample covers around 50.000 firms operating in all economic sectors from 1996 to 2003. They are all *limited* firms facing a legal obligation to deposit their annual accounting at the Chambers of Commerce. Reliability is checked by CEBI itself, and only balance sheets written in conformity with the IV EEC directive enter the sample. We had access to a subset of variables intended to capture different industrial and financial characteristics of the firms under study: Total Sales (TS), Value Added (VA), Gross Operative Margin (GOM), Number of Employees (L), Gross Tangible Assets (K) and Return over Investments (ROI). The list is completed by an index of "financial risk" which *Centrale dei Bilanci* builds using informations from both the balance sheets themselves and external sources, with the explicit aim of producing a synthetic assessment of firms' financial situation. This rating procedure assigns each firm, in each year, a score from 1 to 9 in increasing order of financial fragility: 1 is assigned to highly solvable and less risky firms, while 9 identifies firms undergoing a serious risk of default. The relative number of firms

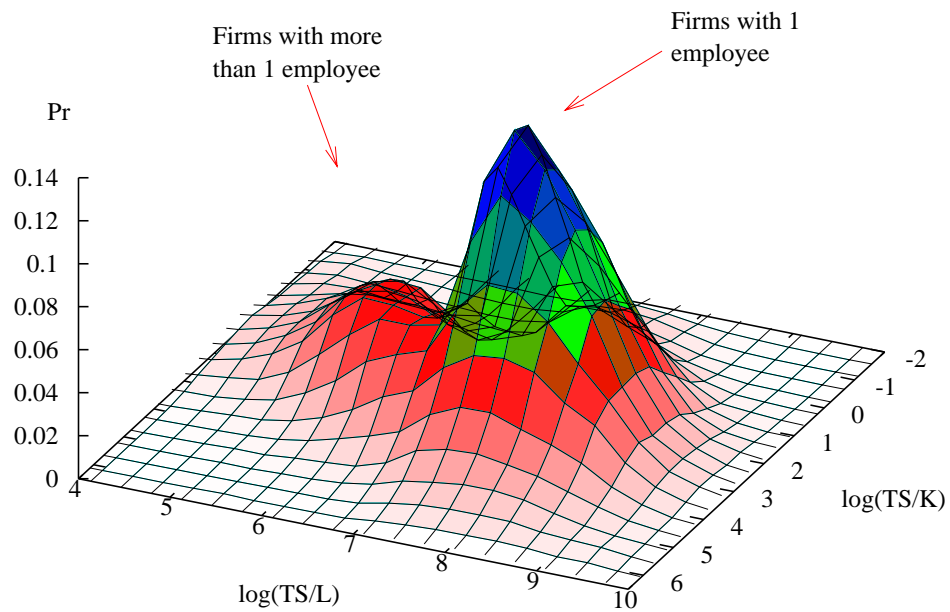
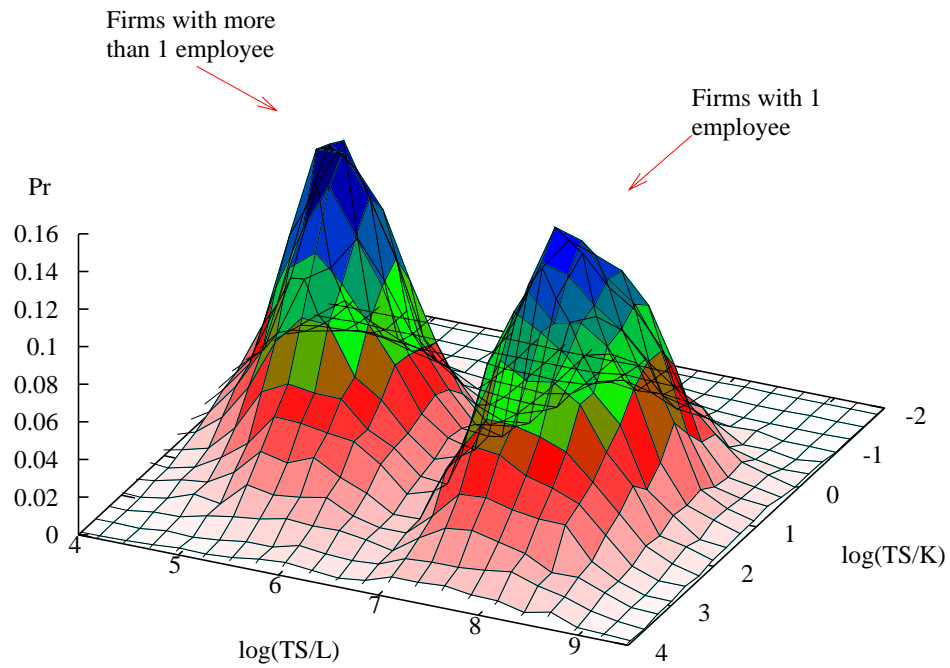


Figure 1: Bivariate empirical density in 2002 of output per worker (Total Sales over Number of Employees) and output per unit of capital (Total Sales over Tangible Assets) in the production of the Manufacturing (**top**) and Service (**bottom**) industry.

belonging to each class remains substantially stable over time, as shown in Table 1, wherein the population of Manufacturing firms in each of the nine rating groups is reported for three different years in the sample. As mentioned, the methodology followed in computing the index has not been disclosed to us, neither in terms of techniques applied nor in terms of variables involved in the computation. To the best of our knowledge, it's widely used by banks when issuing credit lines, and will therefore be regarded also as a meaningful proxy of firms' access to credit. To simplify the subsequent analysis, we reduced the number of rating classes to three, grouping firms into Low Risk firms (with rating 1-3), Mid Risk firms (with 4-7) and High Risk firms (with 8-9). The division is made with the purpose of building groups of firms with similar risk profiles. The present work consists in a series of econometric analysis, run separately on each class. By comparing the obtained results, we shall investigate whether and to what extent financial stability is associated with various measures of industrial performance.²

A second dimension we are interested into concerns the identification of possibly diverging patterns across different sectors of activity. We focus here on comparing Manufacturing and Services, in terms of firms' Ateco code of principal activity, the classification adopted by the Italian statistical office and substantially corresponding to the European NACE 1.1 taxonomy. Codes from 15 to 36 identify the Manufacturing industry, while the Service industry encompasses codes from 50 to 74.

The original data were filtered according to three criteria. *First*, we limited the time span considered to the period 1998-2003. Previous years were discarded, as they recorded a substantially lower number of firms, and we preferred working with similar sample size for the different years under analysis. *Second*, we excluded from the analysis all the firms with less than two employees. The cut was decided on the basis of several reasons. Specifically, we thought this was a simple and effective way to identify "true" firms, that is business entities characterized by a minimum level of organizational structure and operation. This is generally not the case for firms with only one employee. Moreover, the latter capture all the phenomena connected with self-employment, which we also wanted to ignore here. Last, on a more "technical" ground, focusing only on firms with more than one employee should keep us safe from observing of statistical properties that are the mere result of aggregating intrinsically diverse phenomena. Indeed, firms with one employee and firms with more than one employee fall into two categories which are, in all probability, representative of two different worlds. An example of how severe this problem might be is presented in Figure 1, where the bivariate empirical densities of Total Sales per worker (TS/L) and per unit of capital (TS/K) are reported for both the Manufacturing and the Service sectors. It is apparent, especially in the case of Manufacturing, that the two groups of firms present completely different structures. This clearly imposes to keep the two groups distinct. *Third*, motivated by a similar attempt of working with "true" firms, we further restricted the sample to those firms declaring, in each year, Total Sales greater than one million of euros.

On the top of these cleaning procedures, we build two different panels, one unbalanced and one balanced. The unbalanced one is intended to maximize the number of firms appearing in each single year for the period under analysis. This results in working with samples of about 15000/20000 firms within Manufacturing and 10000/15000 within Services, depending on the year. On the other hand, the balanced panel is built with the explicit purpose of avoiding a number of complications arising from attrition and self-selection bias when we

²We took explicitly into account the lower discriminatory power of the class 7 "risk", emerged during our discussions with Unicredit, and we decided to cautiously include it in the Mid-risk class. Sensitivity to different grouping has been explored, in particular, with respect to putting class 7 together with classes 8 and 9, and results didn't change.

Class	Rating	Definition	Number of firms		
			1998	2000	2002
Low	1	high reliability	1114	1396	1531
	2	reliability	1293	1602	1664
	3	ample solvency	1483	1698	1671
Mid	4	solvency	4170	4549	4310
	5	vulnerability	2360	2621	2405
	6	high vulnerability	1969	2016	2083
	7	risk	2249	2691	2311
High	8	high risk	350	433	457
	9	extremely high risk	93	121	130
Total			15081	17127	16562

Table 1: Number of firms, total and by rating classes in 1998, 2000 and 2002 - Manufacturing.

apply standard panel data methods to the analysis of productive structures. Accordingly, there will be considered only those firms for which the figures on the relevant variables are available for the entire time span 1998-2003. The number of firms reduces to 9450 in the Manufacturing sector and to 5174 in the Service sector.

3 Profits and Profitability

The ability of generating profits is a crucial measure of revealed corporate performance. This is true no matter whether one has in mind a simple static model wherein, as it is commonly assumed, firms maximize profits *per se* or more dynamic representation of firms' behavior wherein profits act as the main internal source of financing investment and growth. In addition, profitability is also likely to influence the availability and the costs of external funding, as it guarantees capital markets that they will see their credit paid back.

Finding an empirical counterpart of this concept is not an easy task. The annual pre-tax income reported in balance sheet data, beyond suffering from distortions due to firms' policies related to lowering taxation, is obviously the result of at least two different dimensions in which firms operate, that is production and financial activities. Though the two are closely linked, when evaluating firms industrial performance one is mainly interested in a measure of profits which, at least in principle, is able to capture only those components that are related to the actual result of production activities. With this important methodological premise in mind, we choose Gross Operating Margins (GOM), that is Total Sales minus cost of *material* inputs, as the most satisfactory proxy for production related profit levels. A possible shortcoming affecting this measure relies in that it does not consider the cost of capital, but reconstructing it from balance sheet data is, in general, difficult and entails a number of arbitrary choices. We preferred to stick with a variable that, though not perfect, has the additional advantage of being as close as possible to what we are in principle trying to measure. Accordingly, our first measure of profitability will be the Return on Sales (ROS) index, computed taking the ratio between GOM and Total Sales, that we interpret as a proxy for operational profits extracted per unit of output sold. Second, we compare the results obtained with these measures of

		GOM					
		Mean			V.C.		
Rating		1998	2000	2002	1998	2000	2002
MANUF.	Low Risk	4061	3973	3587	3.61	3.8	3.46
	Mid Risk	1983	1954	1922	4.49	4.82	5.32
	High Risk	-718	701	-2718	-19.40	22.35	-22.66
	Total	2420	2464	2236	4.51	4.68	7.19
SERV.	Low Risk	3474	2153	1723	17.62	11.26	4.66
	Mid Risk	4049	2673	2879	35.3	33.45	32.15
	High Risk	-748	-5585	-52.28	-9.79	-18.73	-411.21
	Total	3692	2147	2409	33.7	36.6	31.5
		ROS					
		Mean			V.C.		
Rating		1998	2000	2002	1998	2000	2002
MANUF.	Low Risk	0.17	0.17	0.15	0.63	0.58	0.68
	Mid Risk	0.09	0.08	0.07	0.75	0.84	1.08
	High Risk	-0.04	-0.04	-0.06	-6.45	-5.4	-3.41
	Total	0.1	0.1	0.09	0.95	0.97	1.16
SERV.	Low Risk	0.09	0.1	0.09	1.4	1.22	1.73
	Mid Risk	0.05	0.05	0.04	3.76	3.27	6.26
	High Risk	-0.02	-0.11	-0.11	-0.14	-3.83	-3.96
	Total	0.05	0.06	0.05	5.54	3.17	5.21
		ROI					
		Mean			V.C.		
Rating		1998	2000	2002	1998	2000	2002
MANUF.	Low Risk	18.12	16.33	15	0.89	0.92	1.07
	Mid Risk	8.18	7.17	5.21	1.72	2.07	4.75
	High Risk	-54.6	-26	-36	-7.06	-3.56	-3.78
	Total	8.67	8.58	6.56	8.39	2.75	5.4
SERV.	Low Risk	19.06	18.86	17.66	0.98	1.27	1.17
	Mid Risk	10.19	9.17	7.4	2.66	3.35	3.09
	High Risk	-36.07	-43.52	-81.44	-7.98	-3.34	-4.51
	Total	10.48	9.53	6.45	6.1	4.43	12.7

Table 2: Mean and variation coefficient of Gross Operating Margin (GOM), Return on Sales (ROS) and ROI in 1998, 2000 and 2002. Figures for GOM are in thousands of Euros, while figures for ROS are in thousands of Euros per unit of output sold.

Rating	Manufacturing		
	1998	2000	2002
Low Risk	34/3882	54/4692	82/4864
Mid Risk	450/10737	580/11869	823/11104
High Risk	219/539	289/588	334/621
Total	703/15151	923/17149	1239/16589
	Service		
	1998	2000	2002
Low Risk	128/2387	200/3302	289/3464
Mid Risk	833/7067	1078/8584	1232/8117
High Risk	196/451	343/586	356/583
Total	1157/9905	1621/12472	1877/12164

Table 3: Number of firms with negative Gross Operating Margin (GOM) over the total number of firms, in different years, by risk class and by sector of activity.

'operations related', with a more standard proxy of profitability directly present in the dataset, that is the Return on Investment (ROI) index. Disaggregating the analyses by sector of activity and risk class, we will investigate the properties of the annual empirical distributions and the autoregressive structure of all of these variables.

Before proceeding it is however instructive to have a look at the figures reported in Table 2. Indeed, they already reveal rather interesting patterns. If one focuses on the numbers computed at the aggregate sectoral level (cfr. line *Total*), one observes an overall stability over time in the average values: this happens for all the three measures, without significant differences between Manufacturing and Services. Despite this, a closer look at the numbers disaggregated by risk class tells a much less stable story: averages for High Risk firms assume always negative values. In terms of GOM, for instance, this means that we are observing firms which, on average, are generating a value added which is not big enough to cover labour costs. Yet weird at first sight, Table 3 confirms that this results are signaling an actual economic phenomenon. Here we show the proportion of firms with negative GOM, disaggregating, again, by risk class: the fraction inside the High Risk firms is so high that it would be difficult to argue that it merely comes from bad reporting or bad data management. Accordingly, we keep all these observations in all the analyses we perform throughout the section.

Empirical distributions of profitability performance

We start by investigating what happens with the ROS, looking at the density of this measure estimated via non parametric (kernel) techniques. This is a way to obtain a smoothed and more robust version of the histogram obtained counting the number of observations falling into separated intervals, so that the estimates can be trusted as providing valuable indications

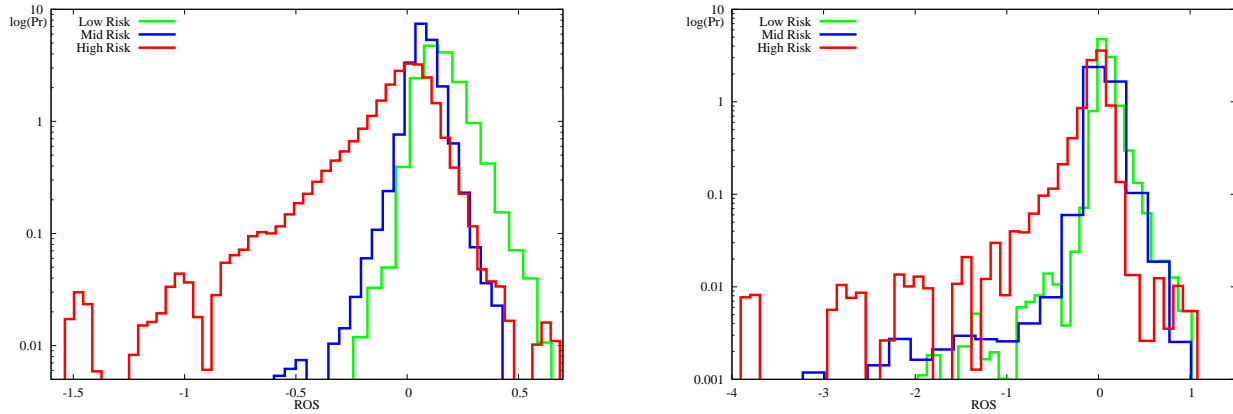


Figure 2: Empirical density of Return on Sales (ROS) in 2002 for the Manufacturing (**left**) and Service (**right**) industry.

about the presence in the data of such features as skewness, fat-tails and multimodality.³ In Figure 2 we plot the results distinguishing by sector of activity and risk class, reporting the estimates for the year 2002 as an example of what is actually observed also over the entire sample. The x -axis reports the observed values of ROS in levels.

As a general message, the plots reveal the presence of widespread heterogeneity: within each risk class, irrespectively of the sector considered, highly profitable firms coexist with poorly performing ones. This is somewhat at odds with one might expect, as the most profitable firms should represent, at least in principle, an attractive and, thereby, less risky investment, while the opposite should hold for badly performing, low profitable ones. Yet, we observe that firms' good or bad records in terms of their ability of generating economic value do not map one to one into good or bad financial rating.⁴

A closer look to the evidence reveals the extent to which the expected ranking in profitability performance is violated. Within Manufacturing, and consistently with Table 3, a clear and distinct pattern is followed by High Risk firms. Negative values are present in all the classes, but the distribution for the High Risk class is much more left-skewed, and, more importantly, presents a relatively big area completely falling into the negative side of the support. Such visual impression of a negative mode is not just an effect caused by the slightly wider support spanned. Recall indeed that on the y -axis we measure the corresponding estimated density: this means that the left-skewed shape for High Risk firms is actually capturing a relevant part of the overall probability mass covered by the observations belonging to this class. This is not the case in the other two classes: the density lies, for the most part, in the positive side of the support and the shape is more symmetric. Though, the distribution for Low Risk firms is slightly shifted to the right, suggesting that, as one might expect, the importance of negative profitability decreases as one moves from Mid Risk to Low Risk firms. A similar ranking is

³These techniques are receiving increasing interest in many areas of applied economic research, as documented, for instance, in a recent review article by DiNardo and Tobias (2001). Here, we use Epanenchnikov kernel and set the bandwidth according to the "rules" suggested in Section 3.4 of Silverman (1986). All the estimates we perform in this work were done using *gbutils*, a package of programs for parametric and non-parametric analysis of panel data. It's distributed under the General Public License, and freely available at www.sssup.it/~bottazzi/software.

⁴The same kind of non trivial relationship emerged also when, in a companion paper (cfr. Bottazzi *et al.* (2006)), we investigated the relationships between financial rating and firms' growth dynamics. We will come back to this point in the last Section.

substantially valid also in the upper part of the distribution. Again, we find that within the Low Risk class there is a relatively higher proportion of firms with above average performance than in the other classes, but, surprisingly, Mid Risk and High Risk firms do not seem to differ that much.

Analogous conclusions can be drawn when one looks at Services. At first sight, the estimated shapes for the three classes appear more concentrated and more similar one to the other than in Manufacturing, but this is just the effect of the different scale employed on the x -axis to cope with the wider support spanned. Netting out this optical effect, what is observed here is that the distribution estimated for High Risk firms is again left-skewed and presents a probability mass in the negative part of the support, relevant and comparable with that observed in Manufacturing. Indeed, in both sectors the biggest part of the mass is represented by an area well approximated by a triangle with base from -0.7 to 0 and height from 0.1 to 3 . Concerning the other two classes, the densities appear quite similar one with the other, and not only in their shapes, but also in the central location: differently from what noted in the Manufacturing industry, the right shift in the distribution of Low Risk firms does not occur here.

We then repeat the exercise estimating the kernel densities of ROI. Table 2 suggests results should be broadly in accordance with those obtained with ROS: negative average values of ROI are indeed concentrated within the High Risk class. The estimated densities plotted in Figure 3 do not contradict this hypothesis.⁵ Let start commenting on the left panel, where we plot results for the Manufacturing sector. Here the most immediate feature to note is the distinctive shape assumed by the distribution estimated for High Risk firms. The range of values touched by the support is quite wide, signaling a relevant degree of heterogeneity within the class, with some firms reaching good performances and others experiencing extremely serious difficulties. And they are not only few: the density is clearly left skewed and most of the probability mass falls into the negative side of the x -axis. Firms with negative ROI are still present, but their proportion is much less relevant inside the other two classes where the shapes appear as more concentrated around a positive mean. Notwithstanding this similarity, Low Risk and Mid Risk firms display sufficiently different properties. The support spanned by the Low Risk firms is wider, the mode is shifted to the right and the overall shape is right-skewed with most of the mass placed at positive values of the x -axis. These features all reveal a higher degree of heterogeneity and better performances with respect to Mid Risk firms. This is expected, but closer inspection of Mid Risk density suggests more than this. When looking at the right part of the distribution, one is confronted with the same kind of puzzle we already observed with the ROS. That is, contrary to what one might expect, best performing Mid Risk firms, that is those reaching the highest value of ROI inside the class, do not do much better than the High Risk ones: the two densities indeed substantially cross each other.

This puzzle do not disappear from the scene when one looks at the empirical distributions of Service firms, plotted in the right panel. Indeed, the shape, the support and the location of the densities are, for each class, almost identical to those estimated for the Manufacturing sector. Again, an intuitive pattern where performance improves with financial rating emerges clearly only in the left part of the distribution. Indeed, at low and negative values of ROI, Mid Risk firms lies in between the other two classes, above Low Risk and below High Risk distributions. On the other hand, at positive values of ROI, the highest proportion of well performing firms is found among Low Risk firms, while the densities estimated for Mid and

⁵The exercise was performed after removing 6 extreme values from a total of 15248 observations in Manufacturing and 10728 in Services.

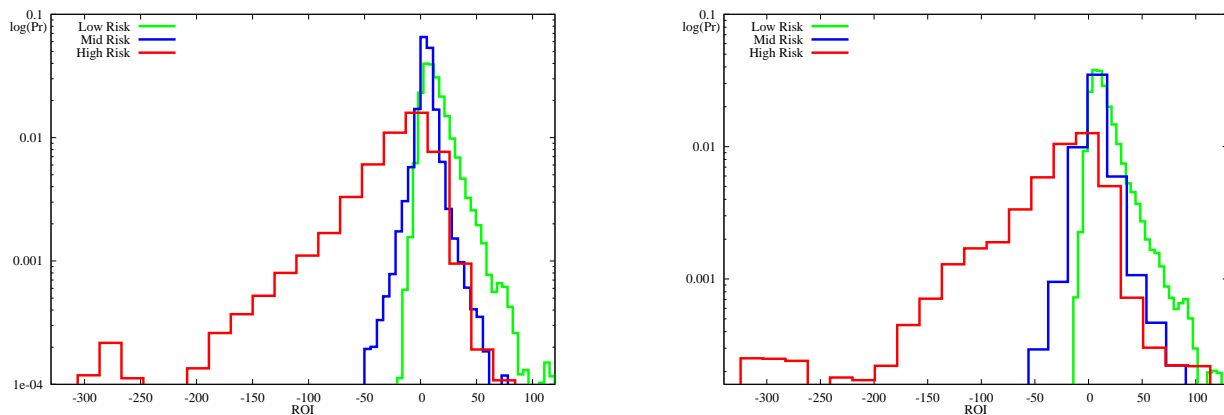


Figure 3: Empirical density of ROI in 2002 for the Manufacturing (**left**) and Service (**right**) industry.

High Risk firms are very similar, again at odds with the ranking that one would expect a priori. The picture becomes even more puzzling when one looks at the right tail, at very extreme levels of good performance: High Risk firms are active here, yet achieving levels of ROI comparable with those attained by Low Risk firms.

Summarizing, a “general rule” has emerged throughout the section: widespread heterogeneity in profitability performances seems a robust property that does not easily map into financial conditions. Though we do not exactly know what is hidden behind the rating index, one might conjecture about the existence of two possible patterns. One the one hand, there are firms which, despite their high, or sometimes outstanding, performance, yet receive bad ratings. On the other extreme, there are some low performing firms that are nonetheless awarded very low levels of financial risk.

Persistence in profits and profitability levels

We have already observed that the shape and the properties of the estimated distributions display substantive stationarity over time. We then turn to quantify the degree of inter-temporal persistence of the variables. The issue is important not only per se, but also with respect to the high level of heterogeneity we uncovered in the previous section. Indeed, evidence of high and positive persistence would suggest that the relative positions of strengths and weaknesses tend to be confirmed over time and, accordingly, heterogeneity in performances tends to reinforce too, at least on average. Starting from seminal work by Mueller (1977), the time series properties of firm profits and profitability have been the object of a bulk of empirical studies, commonly referred to as the ‘persistence of profits’ (PP) literature.⁶ The widespread interest received by the question about whether company profits do converge to a common value or, rather, persistently differ over time was primarily driven by the implications in terms of testing perfect contestability of markets: persistence was indeed interpreted, implicitly or explicitly, as revealing of how effectively free entry and competition were operating in reality. In turn, there were also important implications for the vivid debate started in between the 70’s and the 80’s about two competing views on the determinants of firm profitability performance.

⁶Mueller (1977) and Mueller (1986) are the first studies in the field, while Mueller (1990)’s book include a collection of work reporting results from different countries. See also Cubbin and Geroski (1987), Geroski and Jacquemin (1988), Schohl (1990), Waring (1996), Goddard and Wilson (1999), Glen *et al.* (2001), Maruyama and Odagiri (2002), Glen *et al.* (2003)

On the one side, the structure-conduct-performance theory of the firm held market structure was the primarily source of firms' behavior and earnings, whereas, on the opposite side, the Chicago view stressed firms specific factors, such as efficiency, as prominent determinant of profits and market share dynamics.⁷ In practice, PP studies usually apply a simple AR(1) model

$$y_i(t) = \beta y_i(t-1) + \epsilon_i(t) \quad , \quad (1)$$

where y_i is obtained subtracting the annual cross-sectional mean from the levels of the variables used to proxy profits or profitability, $Y_i(t)$, so that

$$y_i(t) = Y_i(t) - \frac{1}{N} \sum_{i=1}^N Y_i(t) \quad , \quad (2)$$

averaging either at country or sectoral level. Such normalization is employed to control for factors affecting performance dynamics common to all the firms and, in addition, allows the researcher to focus on persistence of deviations from 'normal' profit rates, which was exactly the object of interest in discussing market contestability. The use of a single equation model is usually justified on the basis of Geroski (1990), who interpret Equation (1) as the reduced form of a system of two equations where the effect of entry on current year profitability is formally explicitated. Equation (1), or simple modifications of that, has been estimated using a number of different measures of profitability on a number of firm level datasets covering different countries and different periods of time. Most of the studies find only very slow reversion to the mean is in place, and, therefore, despite some variations in the value of the autoregressive coefficients, they all conclude that persistence in profitability levels is very high.⁸ We test whether this is the case also in our dataset, estimating equation (1) on our three proxies (GOM, ROS and ROI), and we ask whether grouping firms according to sector of activity and financial conditions can add something to the bulk of existing evidence.

The estimation strategy is as follows. After normalizing the variables for yearly sectoral means, we stack all the observations present in each group for the period 1998-2003, so that the longitudinal dimension of the data is exploited to counter-balance the biases possibly arising from the relatively short time dimension. Then, we control for serial correlation in the error terms $\epsilon_i(t)$ applying the approach developed by Chesher (1979) in the context of firm size dynamics. Accordingly, we assume $\epsilon_i(t)$ follows an AR(1) process

$$\epsilon_i(t) = \rho \epsilon_i(t-1) + u_i(t) \quad , \quad (3)$$

where $u_i(t)$ are *i.i.d.* disturbances, so that (1) is rewritten as

$$y_i(t) = \gamma_1 y_i(t-1) + \gamma_2 y_i(t-2) + u_i(t) \quad , \quad (4)$$

with $\gamma_1 = \beta + \rho$ and $\gamma_2 = -\rho\beta$. Since non-robust techniques, such as OLS, can have undesired sensitivity to outlying points, the γ parameters are estimated using Least Absolute Deviation (LAD) regression (Huber, 1981), obtained by minimizing the mean absolute deviation of residuals rather than their mean square deviation. Lastly, we control for heteroskedasticity

⁷See Slade (2004) for a survey on competing models of firm profitability, and McGaham and Porter (1999) for a recent advance in the empirical implications of that debate.

⁸Recent advances in the field are somewhat reverting from such a simple estimation methodology, mainly because of concerns raised by possible endogeneity of firms growth. Goddard *et al.* (2004) and Coad (2005) are two examples, but we will come back to this in Section 5 when we will discuss the relationships among profitability, efficiency and growth.

applying a standard jackknife correction (cfr. MacKinnon and White, 1985) to the estimate of the variance and covariance matrix of the γ estimates $(\sigma_{\gamma_1}^2, \sigma_{\gamma_2}^2, \sigma_{\gamma_1\gamma_2})$. The parameters β and ρ are identified through

$$\beta = \frac{1}{2} \left[\gamma_1 + \sqrt{\gamma_1^2 + 4\gamma_2} \right] \quad \rho = \frac{1}{2} \left[\gamma_1 - \sqrt{\gamma_1^2 + 4\gamma_2} \right] \quad (5)$$

with corresponding errors easily obtained propagating $(\sigma_{\gamma_1}^2, \sigma_{\gamma_2}^2, \sigma_{\gamma_1\gamma_2})$ to β and ρ via the Taylor's expansion of (5).⁹

In Table 4 we present the estimated values of β , broken down by sectors and financial rating groups. As it is well known, a theoretical value of $\beta = 1$ identifies an integrated process, that is a stable pattern of evolution where there are no changes in performance over time apart from unpredictable shocks. Values $\beta < 1$, on the other hand, suggest that the underlying process is one where performance presents reversion to its mean value: at least on average, both best performing and bad performing firms have a probability of converging to the mean performance. In particular, the smaller is β and the faster is the pace of convergence.

Overall, the results confirm our expectations and are in accordance with the conclusions reached within the PP literature, but distinguishing between sector of activity and among rating classes capture some interesting variation in the extent of persistence. We first comment on Manufacturing. At the aggregate level (cfr. line *Total*), the coefficient is $\beta = 0.9982$ with a standard error of 0.0003 when looking at GOM. This is of course not statistically equal to 1, but given the short time window we are using, there are good reasons to consider 1 as a good approximation and, thereby, to conclude that we are observing an integrated process: firms profits, at least as proxied by GOM, follow a pattern with no reversion to the mean. This is no longer true when one considers ROS and ROI. The estimated coefficients are both significant and assume values $\beta = 0.8839$ and $\beta = 0.6306$, respectively: reversion to the mean is actually in place for both the measures, though faster for ROI.

Disaggregating by rating classes adds major insights. Indeed, estimates performed using GOM and ROS reveal the existence of a clear differentiation of patterns among classes. The autoregressive coefficient, read together with its standard error, increases as the financial rating decreases: the extent of persistence, in both the variables, is higher for Low Risk firms, and decreases moving from Mid Risk to High Risk firms. More precisely, Low Risk firms either are characterized by an integrated process, as it is the case for GOM, or follow a very slow process of reversion to the mean, as it happens looking at ROS, while both the Mid Risk and the High Risk group display reversion to the mean, irrespectively of the proxy used and faster in the latter class. This is particularly important when one recall Table 2, where we show that the mean values for both GOM and ROS were extremely low, actually negative, within this class. When looking at ROI, one still observes Low Risk firms following the most persistent pattern, but here the evidence suggests that reversion to the mean occurs in all the rating classes, with High Risk firms again converging faster than the others to their negative average.

Turning to the Service sector, results at the aggregate level confirm the picture emerged for Manufacturing firms: the estimated β is $\simeq 1$ for GOM, suggesting highly persistent (integrated) dynamics, while Profitability and ROI both exhibit reversion to the mean, once again faster for ROI. At the level of risk classes, results are less clearcut than in Manufacturing with respect to how different classes are ranked. When focusing on GOM, the coefficients are $\simeq 1$

⁹We also tried to add additional lags, but in all the exercises we found that the AR(2) coefficient was never statistically significant, in line with results found in Geroski and Jacquemin (1988) and in Glen *et al.* (2003). Therefore, after checking the sensitivity of the AR(1) coefficient β to including or not the AR(2) term, we decided to stick to the simplest model.

		AR(1) - Autoregressive Analysis	
Variable	Rating	Manufacturing - Levels	Service - Levels
GOM	Low Risk	1.0420 0.0006	1.0788 0.0001
	Mid Risk	0.9843 0.0004	1.0394 0.0001
	High Risk	0.5221 0.0091	nan nan
	Total	0.9982 0.0003	1.0556 0.0001
ROS	Low Risk	0.9105 0.0027	0.9627 0.0022
	Mid risk	0.8127 0.0022	0.9104 0.0010
	High Risk	0.7575 0.0272	0.7632 0.0073
	Total	0.8839 0.0016	0.9209 0.0009
ROI	Low Risk	0.7608 0.0043	0.8106 0.0041
	Mid Risk	0.4851 0.0025	0.5110 0.0020
	High Risk	0.6871 0.0286	0.9236 0.0695
	Total	0.6306 0.0014	0.5944 0.0022

Table 4: Estimates of the AR(1) coefficient β in (1) together with their robust standard errors.

for all the classes, exactly in line with the aggregate picture. The pattern of reversion to the mean observed for the ROS at the aggregate level occurs at faster pace for High Risk class, and seems slowing down for Mid Risk and High Risk firms. This happens differently with the ROI index, where High Risk firms are those for which the highest value of β is estimated, even if a close look at the standard errors suggests a substantial similarity with Low Risk firms.

4 Structure of production and productivity performance

Somewhat simplifying, earning of profits signals that a firm is succeeding along two closely interrelated objectives: it is offering goods or services that are wanted by consumer, and it is doing so in an economically viable and efficient way.¹⁰ In this section we provide some initial evidence on this second, supply side, dimension under two respects. First, we seek to characterize firms' structure of production, discussing the degree of heterogeneity in the amount of the two basic inputs used (labor and capital), their combination into production and their contribution to the output of the different firms. Second, and relatedly, we analyse firms' efficiency performance in terms of productivity, mainly focusing on productivity of labour and productivity of capital.

¹⁰Of course, firms might increase profits not only by increasing efficiency, but also creating room for monopolistic behavior. Such strategies are outside the scope of this work, at least at this stage of the analysis

		Total Sales					
		Mean			V.C.		
		1998	2000	2002	1998	2000	2002
Rating							
MANUF.	Low Risk	25713	26708	23751	4.11	4.9	3.01
	Mid Risk	23624	24464	27692	3.87	4.45	4.72
	High Risk	15569	23608	27692	2.88	4.3	13.78
	Total	23877	25049	27309	3.94	4.6	6.29
SERV.	Low Risk	31523	30192	22200	7.75	13.65	4.33
	Mid Risk	33567	31634	34240	10.84	9.09	7.93
	High Risk	16479	21750	22836	2.12	3.89	7.23
	Total	32282	30784	30256	10.21	10.32	7.62
		Number of Employees					
		Mean			V.C.		
		1998	2000	2002	1998	2000	2002
Rating							
MANUF.	Low Risk	114.6	103.4	94	3.28	3.49	2.7
	Mid Risk	105.7	97.1	102.3	3.37	3.14	3.29
	High Risk	101.2	120.9	150.6	3.25	3.46	8.19
	Total	107.9	99.7	101.7	3.34	3.26	3.83
SERV.	Low Risk	71.9	74.7	75.3	0.67	0.78	0.76
	Mid Risk	51.25	52.1	53.5	0.55	0.69	0.75
	High Risk	29.1	26.1	29.2	1.87	1.79	1.68
	Total	55.8	57.4	59	0.66	0.79	0.80
		Assets					
		Mean			V.C.		
		1998	2000	2002	1998	2000	2002
Rating							
MANUF.	Low Risk	13543	13861	13529	5.45	6.23	5.69
	Mid Risk	10545	10972	12458	5.58	5.58	5.61
	High Risk	6063	7718	17075	5.53	4.63	8.91
	Total	11156	11651	12945	5.59	5.87	5.92
SERV.	Low Risk	8679	7081	4552	17.4	18.71	7.4
	Mid Risk	35372	21434	26386	35.45	34.68	35.38
	High Risk	3770	6378	13370	7.13	10.21	15.01
	Total	27423	16902	19532	38.64	36.67	39.11

Table 5: Mean and variation coefficient of Total Sales, Number of Employees and Tangible Assets in 1998, 2000 and 2002. Figures for Total Sales and Tangible Assets are in thousands of Euros.

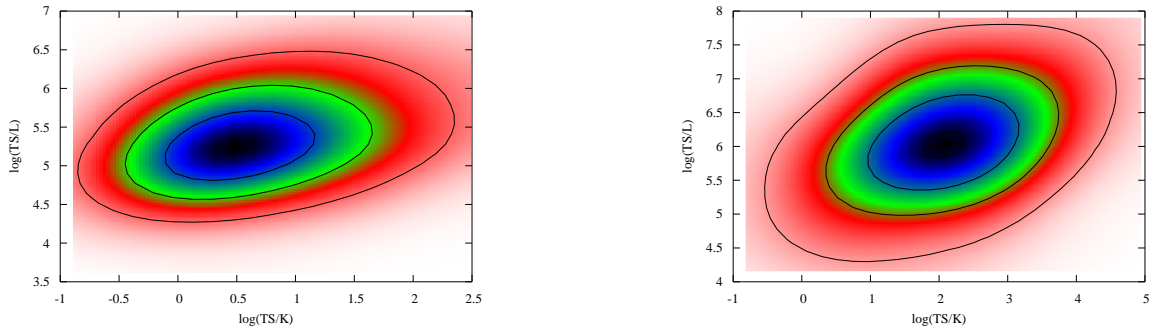


Figure 4: Contour plot of the joint kernel density in 2002 of (log) output per worker and per unit of capital, as proxied by Total Sales over Number of Employees (TS/L) and over Tangible Assets (TS/K), respectively: “Low Risk” firms in Manufacturing (**right**) and Services (**left**).

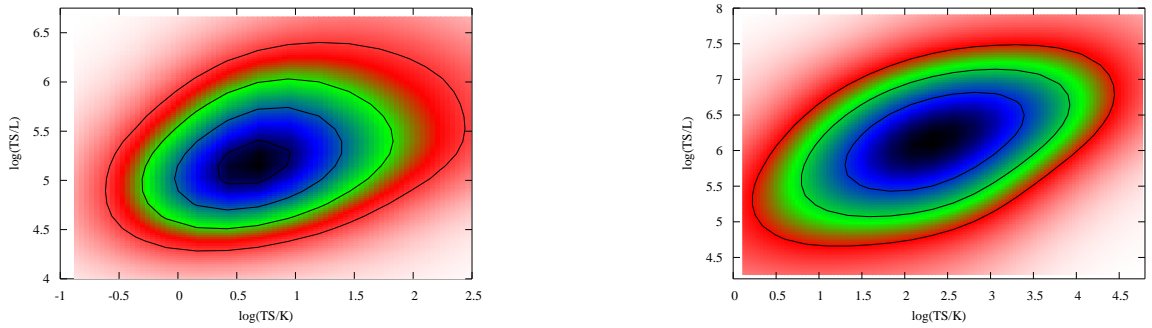


Figure 5: Contour plot of the joint kernel density in 2002 of (log) output per worker and per unit of capital, as proxied by Total Sales over Number of Employees (TS/L) and over Tangible Assets (TS/K), respectively: “Mid Risk” firms in Manufacturing (**right**) and Services (**left**).

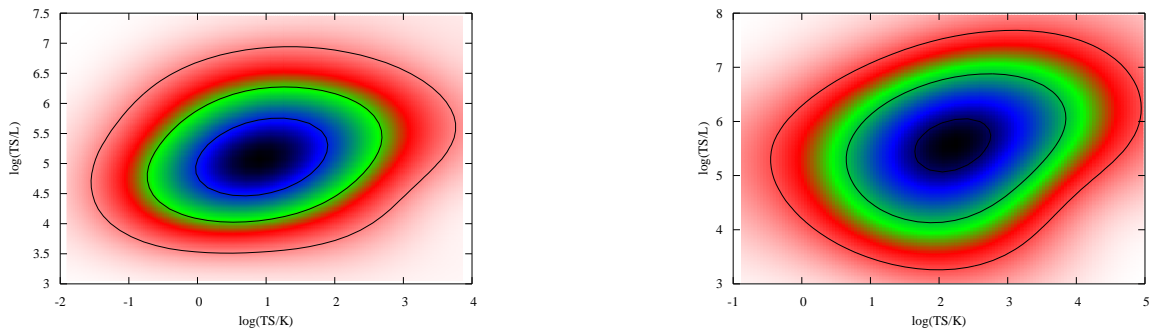


Figure 6: Contour plot of the joint kernel density in 2002 of (log) output per worker and per unit of capital, as proxied by Total Sales over Number of Employees (TS/L) and over Tangible Assets (TS/K), respectively: “High Risk” firms in Manufacturing (**right**) and Service (**left**).

Empirical distribution of productive structures

A first question here concerns collecting evidence on a basic feature about production structures, that is how, and how differently, basic inputs are combined into the production process. We use Total Sales (TS) as a proxy of output, Number of Employees (L) as a proxy of labour inputs, and Tangible Assets (K) as a proxy for capital inputs.¹¹ Specifically, we focus on two measures, output per worker and output per unit of capital. As in the previous analyses, we are particularly interested in the possible emergence of significantly different patterns between sectors and across risk classes. At each of these levels of aggregation and for each year in the sample, we perform non parametric (kernel) estimates of the joint probability density of observing firms characterized by different combinations of output per unit of inputs. Given the stationarity that we observed in the results over time, in Figure 4, Figure 5 and Figure 6 we depict the contour plots of the bivariate densities only for 2002: for each class, the left panel concerns Manufacturing and the right panel describes Services. Each point on the plane represents an observed couple of $\log(TS/L)$ and $\log(TS/K)$, while the scale of colors assigns to each point the corresponding probability density of firms that is estimated to display that particular combination. We also plotted the level curves to help identifying the main patterns.

Results are instructive under many respects. First, the supports of the distributions are all rather wide and span several orders of magnitude, for both output per worker and output per unit of capital. Though somehow expected, as we are not going deeply into sectoral disaggregation, this is a robust property that emerges irrespectively of the particular sector or risk class considered, and points toward the existence of widespread heterogeneity: within each class and within each sector one finds firms organizing their production processes in quite different ways. Second, such heterogeneity does not occur with the same characteristics across industries. On the one hand, the modes of the various distributions estimated for manufacturing firms occur, in different risk classes, at similar values of both the measures, and the ranges spanned in the different classes are similar, too. On the other hand, the densities estimated for services firms present modes occurring at higher values of both the measures and wider supports, suggesting that, broadly speaking, these firms display a tendency toward relatively more heterogeneous production structures and relatively higher values of output-inputs ratios.

Looking for additional insights, we apply a simple linear fit to the data, estimating the model

$$\log(TS/L)_i = a \log(TS/K)_i + b + \epsilon_i \quad (6)$$

The slope coefficient a yields a measure of the elasticity of substitution between labour and capital inputs. That is, assuming homogeneity of production technology among firms, one captures here how labour should adjust in response to small variations in capital, if the same level of output has to be maintained. Table 6 reports the estimated values of a .

The results confirm what visual inspection of the plots could already suggest: the two measures are everywhere positively correlated, with a slightly lower effect estimated among

¹¹Table 5 reports descriptive statistics about these variables. Two choices deserve a short comment. First, even if it is often argued that Number of Employees is usually badly reported, we are nevertheless confident that most of the problem has been absorbed by the initial decision to restrict the attention only to firms with more than one employee. Second, as for Tangible Assets, we preferred to use gross, rather than net, figures, because this choice should keep us safe from distortions related to accounting policies aiming at lowering taxable income.

Rating	Manufacturing	Services
Low Risk	0.302 0.011	0.307 0.013
Mid Risk	0.302 0.006	0.389 0.008
High Risk	0.218 0.03	0.294 0.03
Total	0.297 0.006	0.367 0.007

Table 6: Estimates of a in (6) by risk class and by sector of activity

High Risk firms in the Manufacturing sector and a slightly higher one among Mid Risk firms in the Service sector.

Input-output relations

Given the observed production structures, we now move to the analysis of firms' production technologies. We are interested in describing how, both within and across sectors or risk classes, the two basic inputs (labour and capital) contribute to output. This is explored performing two different exercises. First, we fit a Cobb-Douglas relationship between output and inputs via parametric techniques, applying different panel data methods. Then, we estimate non parametrically the conditional expectation of output given a certain combination of inputs. We recall that in order to avoid self selection or attrition problems possibly affecting the parametric exercise, we built a balanced panel including only firms for which figures on the relevant variables were available for the *whole* time window 1998-2002. To keep comparability of results, all the analyses are performed on this sample of firms.

Parametric analysis

We begin describing the production process parametrically. We fit the model

$$s_{i,t} = \beta_l l_{i,t} + \beta_k k_{i,t} + u_i + \epsilon_{i,t} \quad (7)$$

where s , l and k are the logarithms of Total Sales, Number of Employees and Tangible Assets, respectively. The coefficients β_l and β_k represent the elasticities of output with respect to the two inputs, while the firm specific terms u_i are meant to absorb the effect of idiosyncratic and unobserved characteristics, at least of those that are not varying with time, as it should be the case for most of the factors we are not including in the regression, especially given the relatively short time window we are observing. This way one hopes to reduce the bias on the relevant coefficients, but, then, a second potential drawback arises: as u_i plays now the role of an additional regressor, OLS unbiasedness would require u_i being uncorrelated with (more precisely, orthogonal to) the error term $\epsilon_{i,t}$. An additional complication arises from the possible presence of heteroskedasticity and/or serial correlation in the error terms.

A number of techniques have been developed in the panel data econometrics literature exploiting the time dimension of the data in order to overcome these potential problems without forsaking the attempt of controlling for unobserved factors.¹² Here, after checking the

¹²The reader is referred to Wooldridge (2000) for a complete exposition of the various techniques, and to

Method	Rating	Parametric regression							
		Manufacturing				Service			
		β_l		β_k		β_l		β_k	
Pooled OLS	Low Risk	0.6427	0.0213	0.1936	0.0168	0.6388	0.0271	0.1654	0.0208
	Mid Risk	0.6052	0.0133	0.2011	0.0102	0.5353	0.0170	0.1673	0.0131
	High Risk	0.7144	0.0708	0.1421	0.0620	0.6309	0.0742	0.1271	0.0757
	Total	0.6181	0.0112	0.1978	0.0086	0.5641	0.0141	0.1630	0.0109
Fixed Effects	Low Risk	0.4247	0.0551	0.1130	0.0299	0.3623	0.0537	0.0470	0.0233
	Mid Risk	0.3513	0.0183	0.0991	0.0112	0.3072	0.0234	0.0899	0.0122
	High Risk	0.3827	0.0868	0.0447	0.0459	0.3089	0.0884	0.0408	0.0473
	Total	0.3701	0.0185	0.1001	0.0117	0.3183	0.0214	0.0789	0.0111
Random Effects	Low Risk	0.5427	0.0278	0.1698	0.0146	0.4549	0.0362	0.0815	0.0201
	Mid Risk	0.4598	0.0139	0.1653	0.0088	0.3798	0.0177	0.1303	0.0098
	High Risk	0.5491	0.0761	0.1056	0.0607	0.4060	0.0676	0.0942	0.0418
	Total	0.4830	0.0125	0.1652	0.0079	0.3970	0.0157	0.1184	0.0089

Table 7: OLS, Fixed effects and Random Effects estimates of the coefficients β_l and β_k in (7), together with their standard errors

robustness of results to different estimation methods, in Table 7, we show only the estimated coefficients obtained applying Fixed Effect (FE) and Random Effect (RE). Pooled OLS are also reported as a benchmark case.¹³ Standard errors are computed applying techniques robust to heteroskedasticity and allowing for within cross-sectional unit serial correlation across time. In line with the general aim of identifying peculiar patterns among firms belonging to different sectors and different risk classes, the model in (7) has been estimated separately at all of these levels. To do so, since firms' rating is in principle allowed to vary from year to year, and given that focusing only on those firms that never change rating class during the period would have caused significant reduction in the sample size, we control for financial conditions assigning the firms according to their ratings in 2002. Further, as an additional control for unobservable factors likely affecting the estimated coefficients, we wash out business cycle and sectoral dynamics type of effects including a full set of yearly and 2-digit sectoral dummies.

Both FE and RE suggests a remarkable degree of homogeneity, at all levels of analysis.

Griliches and Mairesse (1995) for a critical survey of the many applications in the context of the present exercise.

¹³In particular, we also applied Between Effects estimation and standard dynamic panel data methods. Results were broadly in line with what we obtained with the methods reported here. Lack of information on intermediate inputs and investment prevented us from using recently developed techniques such as those proposed in Olley and Pakes (1996) and Levinsohn and Petrin (2003).

Overall, the most apparent result is that the estimated elasticity of output to labour inputs is always higher than the elasticity to capital inputs. In addition to this, there are no statistically significant differences, nor in β_l neither in β_k , across sectors and classes: once the coefficients are properly read together with their standard errors, the value of β_l and β_k are very similar along all the dimensions. The only exception is found for the elasticity to capital in the High Risk class, which is not statistically significant, but such a weird result is likely due to 'technical' reasons. It is indeed not uncommon (see Griliches and Mairesse (1995)) to observe a tendency, especially for the elasticity of output to capital, to rapidly lose significance as the number of observations considered reduces: Table 1 suggests this is what happens in our sample with the High Risk class.

Non parametric analysis

A major weakness inherently affecting the standard production function approach rests in that a single functional form, and hence a single production technology, is by construction assumed to be common to all the firms. Motivated by the significant heterogeneity in production structures documented above, we preferred to couple standard econometric techniques with non parametric exercises which do not require stringent assumptions, and seems better suited to deal with such heterogeneity.¹⁴

Using the balanced panel we perform, for each year in the sample, a multivariate estimation of the conditional expectation of output for given combinations of inputs. Applying kernel techniques, smooth surfaces have been obtained from the discrete set of observation distinguishing, as usual, among Manufacturing, Services, and the three risk classes. These are plotted in Figure 7, Figure 8 and Figure 9, for the year 2002. Each point on the surfaces relates the combinations of labour and capital inputs, reported respectively on the x and y axes, with the corresponding estimated level of expected output, reported on the vertical axis. To improve readability, we also draw some level curves on the basis of the various plots, connecting the various input mixes that generate the same level of output. The use of a logarithmic scale, allowing to represent on the same plot firms employing very different levels of inputs, goes in the same direction of helping the reader in identifying the relevant patterns.¹⁵

A first one, common to all the graphs, identifies output as an increasing function of both labour and capital: at least globally, a positively sloping plane in the (s, l, k) space is a good proxy for the displayed surfaces. This is an expected result that can be read as analogous to the positive signs assumed by the coefficients a estimated parametrically from the linear fit in (6) and reported in Table 6. Second, we still observe the widespread heterogeneity in technology revealed by the analysis of empirical probability densities conducted in Figure 4, Figure 5 and Figure 6: within and across sectors and risk classes the same level of output is attained with quite different combinations of inputs. This is particularly true for smaller firms: indeed for lower levels of both inputs one observes a flat and wide plane. Finally, though not shown here for a matter of space, substantially identical results emerged during the analysis

¹⁴Actually, there are also other substantive reasons suggesting that production functions provide, at best, only a quite naive approximation of firms' operation. The point has been repeatedly raised in the history of economic theory, mainly by scholars of economics of knowledge and technical change (see, among the many contributions, the classical work by Nelson and Winter (1982) and the forthcoming paper by Winter (2006) for an alternative, evolutionary-neo schumpeterian view of the firm, and the discussion in Dosi and Grazzi (2006)), but it has also been at the center of the debate during the so-called *Cambridge controversy* on the theory of capital.

¹⁵See Bottazzi *et al.* (2005a) for technical details and an application to a different dataset on Italian firms, with similar results.

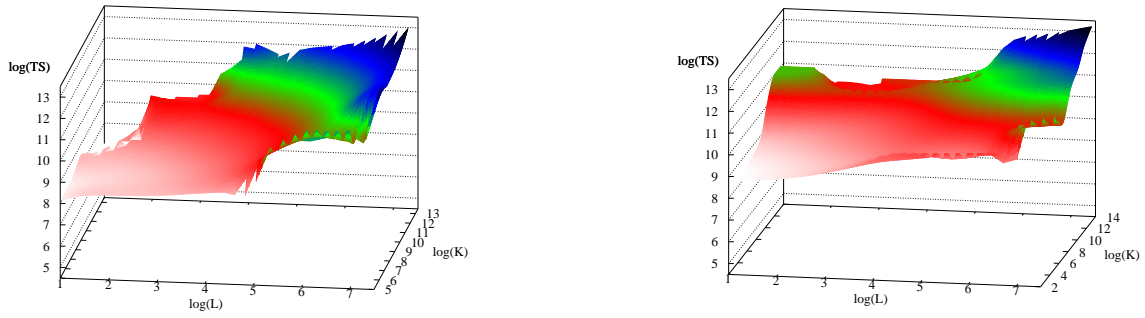


Figure 7: Kernel estimate of the conditional expectation of output (Total Sales) in 2002 for “Low Risk” firms in Manufacturing (**right**) and Service industry (**left**).

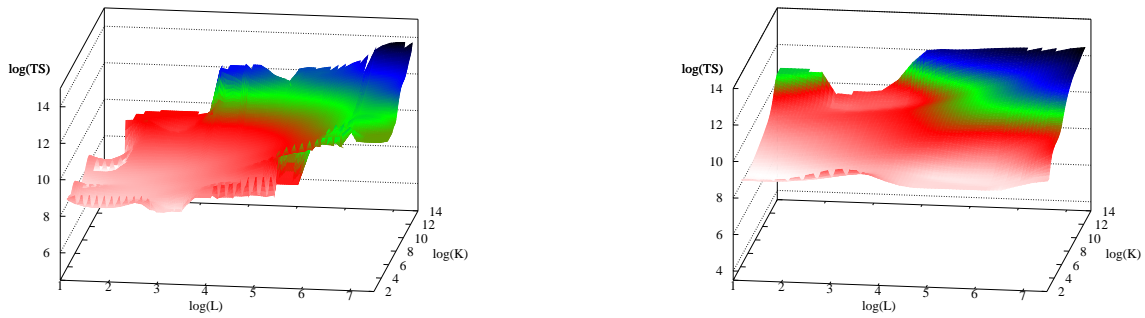


Figure 8: Kernel estimate of the conditional expectation of output (Total Sales) in 2002 for “Mid Risk” firms in Manufacturing (**right**) and Service industry (**left**).

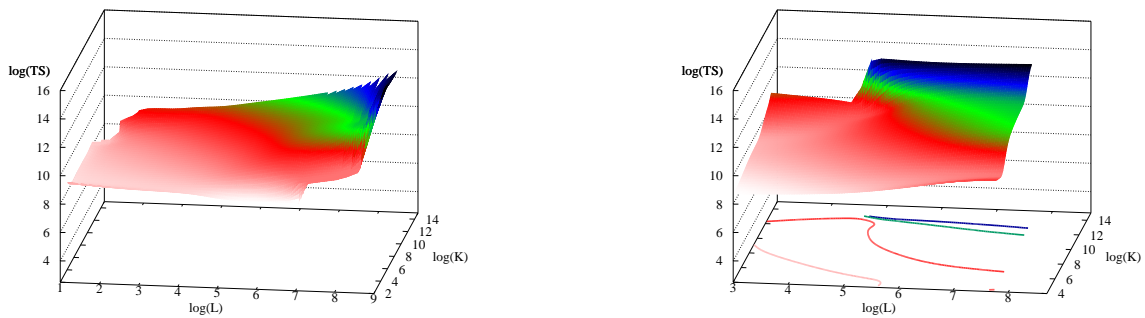


Figure 9: Kernel estimate of the conditional expectation of output (Total Sales) in 2002 for “High Risk” firms in Manufacturing (**right**) and Service industry (**left**).

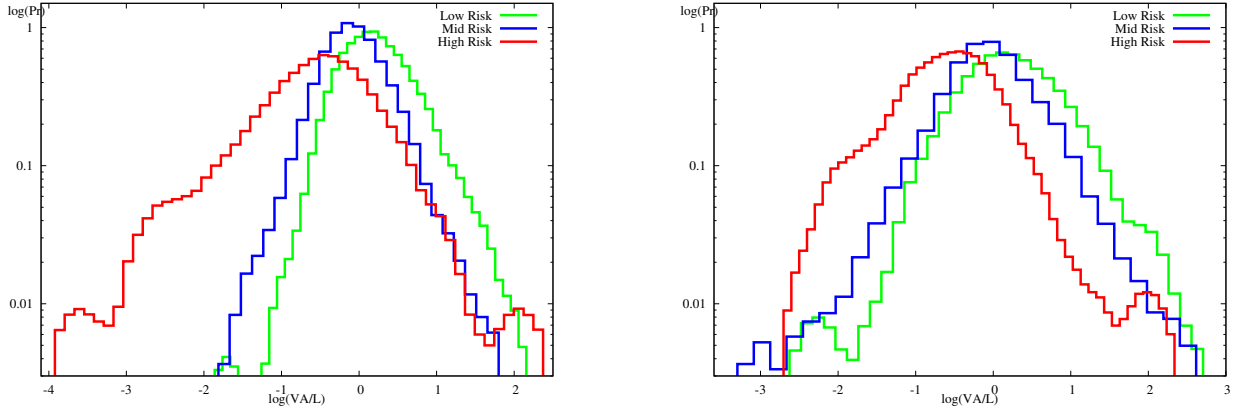


Figure 10: Empirical density of Labour Productivity in 2002 for the Manufacturing (**left**) and Service (**right**) industry. Labour Productivity is defined as Value Added over Number of Employees (VA/L).

also for the other years included in the panel, suggesting that heterogeneity is not only wide but also persistent over time.

Productivity

We complete the picture about firms' production structure exploring how efficiently inputs are used in production. The existing empirical literature on this topic, stimulated by the increasing availability of large panel datasets, is huge. The questions addressed are many. Just to cite but a few, they range from discussions around measurement problems, to the degree of heterogeneity in firms' and plants' productivity, the associated degree of persistence over time, the identification of its major determinants, the impact on firm turnover and the relationship between the latter and aggregate economic variables such as growth and employment. Bartelsman and Doms (2000) , Ahn (2000), Tybout (2000) and Foster *et al.* (2001) offer excellent reviews and systematizations of the results. In parallel with what did above concerning profitability, this section asks whether sectoral and risk class disaggregation can help adding information about the existing empirical evidence on two issues: the properties of the empirical distribution of firms' efficiency and its persistence over time. We will mainly focus on two different measures, that is Labour Productivity, defined as Value Added per employee, and Capital Productivity, computed as Value Added divided by (Gross) Tangible Assets.¹⁶

Productivity distributions

For each year in the sample, we take our balanced panel and estimate the empirical (kernel) density functions of Labour and Capital Productivity, looking at *relative* performance with respect to sectoral averages

$$y_i^X(t) = \ln(Y_i^X(t)) - \frac{1}{N} \sum_{i=1}^N \ln(Y_i^X(t)) \quad x \in \{VA/L, VA/K\} \quad . \quad (8)$$

Given the stationarity observed in the results over time at every level of aggregation, we show and comment only the estimates for 2002.

¹⁶Cfr. Table 8 for basic descriptive statistics.

		Labour Productivity					
		Mean			V.C.		
		1998	2000	2002	1998	2000	2002
MANUF.	Low Risk	79.7	66.5	61.6	5.44	5.57	4.95
	Mid Risk	151.5	125	123.7	19.2	18	15.8
	High Risk	82.8	106.4	89.3	4.13	4.85	4.4
	Total	130.9	108.5	104.3	18.9	17.3	15.38
SERV.	Low Risk	83	83.3	84.9	1.62	1.3	1.54
	Mid Risk	63.1	61.1	56	9.02	7.2	1.24
	High Risk	29	22.5	22.4	2.47	5.13	6.16
	Total	66.3	65.2	62.6	7.3	5.69	1.54
		Capital Productivity					
		Mean			V.C.		
		1998	2000	2002	1998	2000	2002
MANUF.	Low Risk	1.21	1.69	1.16	2.58	18.24	2.30
	Mid Risk	1.52	1.1	1.29	15.24	4.38	12.25
	High Risk	2.65	1.2	1.24	8.73	2.83	3.52
	Total	1.48	1.26	1.26	13.71	13.04	10.58
SERV.	Low Risk	3.45	5.18	2.82	4.98	15.56	3.38
	Mid Risk	2.65	3.17	3.04	5.61	13.23	9.87
	High Risk	2.11	2.55	2.74	3.67	3.88	3.74
	Total	2.81	3.65	2.97	5.41	14.71	8.59

Table 8: Mean and variation coefficient of Labour Productivity and Capital Productivity in 1998, 2000 and 2002. Figures are in thousands of Euros per employee and per unit of capital, respectively.

We begin commenting about Labour Productivity distributions, reported in Figure 10. A first interesting issue concerns whether there are differences in the behavior across the two sectors. Under this respect, one immediately observes Low Risk and Mid Risk firms displaying higher heterogeneity within Services than within Manufacturing, while High Risk firms present a more similar heterogeneity across the two sectors. Indeed, the estimates for Low Risk and Mid Risk firms in the Manufacturing sector are similar to those obtained in the Service sector for what concerns the shape, but much more concentrated around average performance.

A second point concerns the comparison across the different classes ratings. Within Manufacturing, the distributions estimated for the Low Risk firms are substantially identical to those estimated for the Mid Risk class, while High Risk firms exhibit a distinctive shape: they reach both the top and the bottom level of performance and present a pronounced left skewness. The left tail behavior is in agreement with what one might expect a priori: among firms experiencing severe financial difficulties the proportion of those characterized by low levels of Labour Productivity is persistently higher than in the other rating classes. On the contrary, the estimates for the right part of the distribution are rather surprising. Indeed, although one would expect the proportion of firms with high level of Labour Productivity to increase as financial conditions improves, the evidence we find here is only partially in agreement with

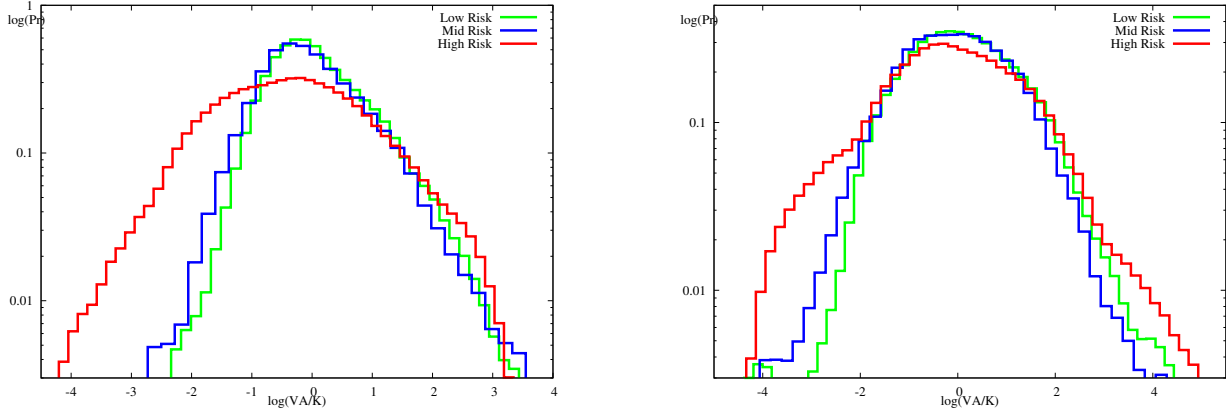


Figure 11: Empirical density of Capital Productivity in 2002 for the Manufacturing (**left**) and Service (**right**) industry. Capital Productivity is defined as Value Added over Tangible Assets (VA/K).

such a conjecture. We observe firms with above average Labour Productivity have a similar weight across Mid Risk and High Risk firms, or even higher for the latter class, especially at the very extreme of the positive side of the supports. The same happens within Services where we still observe some High Risk firms which are able to outperform the others.

At this stage of the analysis one can only propose tentative interpretations. One possibility is of course that some High Risk firms are simply dismissing their activities as an answer to their difficulties: in this case high Labour Productivity would simply be a statistical artifact recording work-force lay-offs. Another possibility could be that among High Risk firms there are some newly created or innovative enterprises which are highly indebted exactly for their particular nature or present state, and are therefore badly rated, but this leave the question open about what kind of firms should the banking system bet on.

The same puzzle shows up again when looking at Capital Productivity distributions, reported in Figure 11. In both Manufacturing and Services we identify a clear pattern: Low Risk and Mid Risk distributions are always quite similar, while the distributions estimated for the High Risk class lie above the other two in both the tails, in a way that is more apparent in the left part, especially for Manufacturing. This suggests that the proportion of firms with very poor and very good performance in Capital Productivity is higher among firms in financial difficulty. The result is qualitatively similar to and quantitatively more relevant than what we observed above for Labour Productivity: the same interpretations can be attempted also here.

As an additional robustness check, we ask whether similar results emerge also when looking at Total Factor Productivity (TFP). We take $u_i + \epsilon_{i,t}$, the residuals from the (Random Effects) parametric estimation performed above in equation (7), and, after subtracting annual sectoral averages, we repeat the kernel estimation exercise. The resulting densities for 2002, shown in Figure 12, are broadly in agreement with what we said for Labour and Capital Productivity, although much more smoothed. The distributions obtained for the Manufacturing display higher asymmetry and span a narrower support than in the Service sector, while the expected one-to-one mapping between financial rating and productivity performance is confirmed, in both the macro-sectors, at below average levels of productivity, but violated in the positive side of the support. The only major peculiarity concerns the shape of the distributions, which are less fat-tailed, and much more similar to a parabola well approximating a Gaussian distribution on the log-log scale we are employing. therefore, and in contrast with what we concluded looking at Labour and Capital productivity, the degree of heterogeneity in performance seems

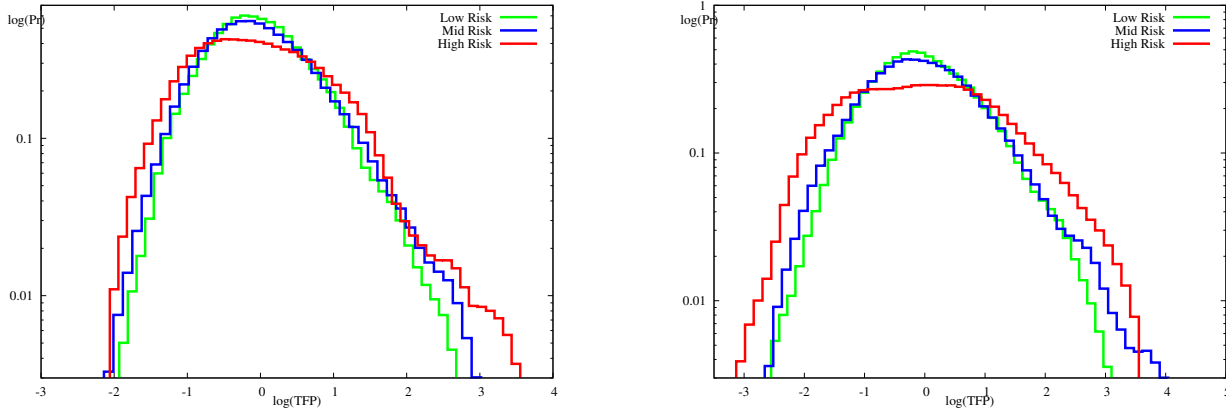


Figure 12: Empirical density of Total-Factor Productivity (TFP) in 2002 for the Manufacturing (**left**) and Service (**right**) industry.

much less pronounced in terms of TFP, both across sectors and across classes. However, this was a somehow expected finding, whose relevance, we believe, is substantially weakened by the parametric nature of TFP estimation: assigning to all firms the same mode of production (a Cobb-Douglas function) by itself absorbs much of the heterogeneity. This is the main reason why we will not explore further the properties of this measure in the remainder of the section.

Summarizing, we find that High Risk firms do not necessarily behave as one might expect a priori. In close similarity to what observed about profitability performance, a simple relationship suggesting that better financial conditions should map one to one into better performance seems not confirmed by the data. In addition, persistent heterogeneity of performance is robustly found at all level of aggregation.

Persistence in productivity performances

Despite the non parametric investigations performed on productivity densities have already suggested a considerable degree of stationarity over time is present for both Labour and Capital Productivity, we still miss to explore the profile of the efficiency performance of each firm over time. We discuss this point looking at the autoregressive structure of both the *levels* and the *growth rates*, for both the productivity proxies.

Concerning the levels, previous studies (see Bartelsman and Dhrymes (1998) and Baily *et al.* (1996)) have established high persistence is a common property, robust to the use of different measures of efficiency and different methodologies. Following the literature, we focus again on relative efficiency, as defined in equation (8), and estimate an AR(1) model

$$y_i^x(t) = \alpha y_i^x(t-1) + \epsilon_i(t); \quad x \in \{VA/L, VA/K\} \quad (9)$$

separately for firms active in Manufacturing and Services, disaggregating by rating classes. The estimation strategy applies the same parametric apparatus we used dealing with persistence in profitability. That is, after stacking all the observations for the period 1998-2003, we apply LAD regressions controlling for serial correlation in the error term $\epsilon_i(t)$ through the techniques developed in Chesher (1979) and we cure heteroskedasticity via a standard jackknife estimator.

The same approach is applied to explore the AR structure of productivity growth, less studied in the past. We estimate the AR(1) process

		AR(1) - Autoregressive Analysis			
		Manufacturing		Service	
Variable	Rating	Levels	Growth	Levels	Growth
Labour Productivity	Low Risk	0.920 0.003	-0.323 8%	0.928 0.004	-0.332 11%
	Mid Risk	0.939 0.004	-0.292 22%	0.958 0.005	-0.281 14%
	High Risk	0.895 0.004	-0.325 9%	0.897 0.004	-0.339 12%
	Total	0.848 0.048	-0.491 19%	0.866 0.045	-0.509 31%
Capital Productivity	Low Risk	0.976 0.003	-0.193 23%	0.971 0.004	-0.259 13%
	Mid risk	0.961 0.002	-0.216 12%	0.966 0.003	-0.216 12%
	High Risk	0.951 0.027	-0.398 21%	0.987 0.031	-0.278 60%
	Total	0.965 0.002	-0.215 10%	0.965 0.003	-0.215 10%

Table 9: Estimates of the AR(1) coefficient α in equation (9) and β in equation (10) together with their standard errors.

$$\Delta y_i^X(t) = \beta \Delta y_i^X(t-1) + \eta_i(t) \quad , \quad (10)$$

where the growth rates are computed as simple log-differences of the levels over time, $\Delta y_i^X(t)$.

Overall, the estimated values of α and β , reported in Table 9, yield a picture where relative productivity is highly correlated in levels and mildly anti-correlated in growth rates: when properly considered together with its standard errors, the coefficient α lies almost always well above 0.9, while the estimates for β , in most of the cases, takes on values ranging in between -0.15 and -0.35 , with only slightly higher figures for both the coefficients in the case we focus on Capital Productivity. The first result suggests that productivity levels attained in one year are strongly dependent on past performances, with reversion to the mean certainly occurring, but very slowly. On the other hand, the evidence on growth rates points toward a tendency to convergence too, but the negative sign in the estimated autocorrelations, though not being very big, tells a story in which persistence of chance is less relevant: past positive growth is likely to be followed by negative growth, and vice-versa.

Given this general picture, not much more information is gained comparing results at sectoral level: the coefficients estimated in the aggregate for Manufacturing and Services are statistically equal. And not much more can be said when controlling for financial conditions, as we do not observe big differences in the estimates performed across the different rating groups, nor for α neither for β . The only exception is represented by the estimates obtained

for High Risk firms, where the first order autocorrelation in the levels, α , is slightly weaker than in the other two classes, for both Labour and Capital Productivity.

5 Conclusion: linking profitability, productivity and growth

In the previous sections we have studied two crucial dimensions of firms' performance and dynamics, and exploit the rating index provided by CEBI to identify their relationship with financial conditions and access to credit. We look at profitability, and, then, we explored the modes and the efficiency with which production of goods and services is actually performed, as the obvious dimensions where generation of economic value finds its "physical" and technical roots. The evidence we gathered has been to a good extent surprising along both the dimensions, as we found that financial conditions do not necessarily improve with economic performance. Admittedly, the picture is far from complete as one would at least consider a third dimension of revealed performance, that is firm growth. The issue, not touched here, has been the object of a companion paper (see Bottazzi *et al.*, 2006) where, employing the same dataset, we performed a number exercises exploring the links between size-growth dynamics and financial fragility. The conclusions broadly supported the overall picture emerging from the present analysis, revealing persistently widespread heterogeneity across firms' growth rates and puzzling relationships between growth and financial rating were found within both Manufacturing and Services.¹⁷ We now supplement the previous analyses with an investigation of the relationships among these three dimensions.

A step forward along this lines not only represents a natural way toward a completion of our research program, but seems particularly appropriate in view of the relative few empirical research done in this direction. Indeed, to our knowledge, applied work on growth, profitability and productivity has mostly developed along three separate strands of literature, and attempts to offer a comprehensive view about the three basic dimensions of firm economic activity and performance have been rare.¹⁸ On the one hand, there are instances of works looking at the relationship between productivity *changes* and growth, with mixed results (see the review in Bartelsman and Doms, 2000), whereas only few studies directly test the correlation between productivity *levels* and growth.¹⁹ On the other hand, the profitability-growth link has also remained relatively unexplored until recently. Goddard *et al.* (2004), using data on a sample of European banks, find profitability to be important for future growth, whereas Coad (2005), performing a similar exercise on French manufacturing firms, draws quite the opposite conclusions. Virtually no work has been done on the productivity-profitability link, on the presumption that physical efficiency should 'naturally' translates into profitability.²⁰

To keep the discussion simple, we will consider here only one variable for each dimension. *First*, firm growth is measured in terms of Total Sales, as it is the most immediate proxy for

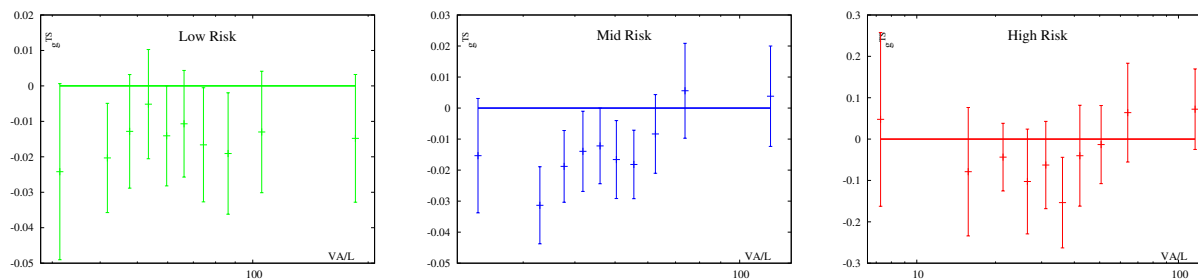
¹⁷We refer the reader to the paper for the details and the literature cited therein.

¹⁸See Dosi (2005) for a significant exception.

¹⁹Bottazzi *et al.* (2005b) didn't find any relationship is in place, while Bottazzi *et al.* (2002) document a positive relationship shows up when growth is measured in terms of number of employees, but disappears when growth is proxied with sales or value added.

²⁰Interestingly, a recent work by Foster *et al.* (2005) cast doubts on the validity of the existing empirical tests about the productivity-growth linkages exactly because failing to disentangle the separate effects of productivity and profitability on growth.

Manufacturing



Service

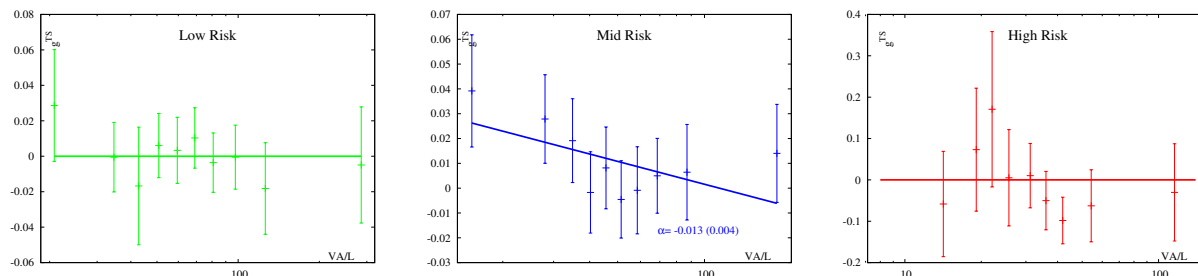


Figure 13: Average growth rate (g^{TS}) as a function of Labor Productivity (VA/L), measured in thousand of Euros of Value Added per employee, for the Manufacturing and Services sectors. Confidence intervals are reported as two standard errors (on each side). If the slope is significantly different from zero ($p < .05$) a linear fit is reported, otherwise the $y = 0$ axis is displayed.

market success.²¹ *Second*, we choose the ROS as a proxy for the ability of the firm to generate economic value. We, indeed, believe that the gross profit per unit of output sold can be considered a reliable indicator of profit, as it does not suffer from the limit of encompassing operations not related with the mere production of goods or services. *Third*, we take Labour Productivity as a simple measure of productive efficiency. This last choice is essentially motivated by what we have learnt in the course of the analysis. We have argued how the alternative definition in terms of TFP is the result of a parametric exercise that, by imposing a unique technology across firms, washes away much of the interesting heterogeneity observed in the actual data. We have also shown how Labour Productivity and Capital Productivity behave quite similarly, both in terms of properties of empirical distributions and in terms of intertemporal dynamics. Analogously to what done in the previous sections, we consider firms disaggregated with respect to sector of activity and financial conditions. All the results we report refer to 2002, by way of example of what we robustly observe for the entire sample period 1998-2003.

We start by comparing Labour Productivity levels with Total Sales growth, asking to what extent firms' ability (or inability) to gain market shares relates with their efficiency in organizing the production process. Textbook economic reasoning tells a story where the two performances should go hand in hand: the more efficient and the less costly its production structure, the more a firm will be able to charge relatively low prices and, thereby, to gain

²¹There are essentially two distinct ways of measuring size and growth. Total annual revenues or the value added generated by annual operations are the standard proxies for realized performances on the market, that is at the market shares the firm owns, while measures such as the number of employees or total assets mainly reflect the potential productive capacity.

market shares. Of course a number of factors are likely to break this simple causal relation going from production efficiency to market success, possibly coming from both demand and supply side kind of effects. From the supply side, firms themselves implement a number of actions capable to affect sales, such as rent seeking or other competition distorting strategies, pricing and mark up over costs policies, choices about factors' remuneration, etc. All of them, in turn, interact with a number of demand side factors, such as the degree of stickiness in consumption choices, brand fidelity, and, more generally, the effect of business strategies creating artificial barriers to the adoption of new products. A priori it is difficult to have a clear idea about the overall effect.

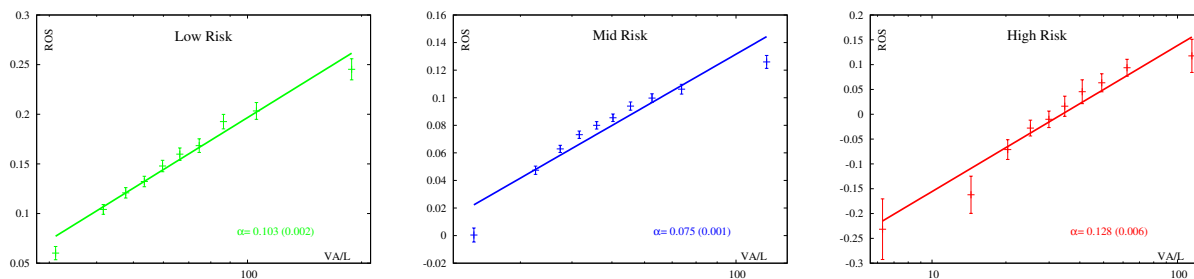
We perform a simple exercise: we divide firms in equipopulated bins according to Labour Productivity, and within each bin we compute the average growth rate g^{TS} , as simple log difference of Total Sales over time. In Figure 13 we plot these averages on the y -axis, together with the associated two standard errors confidence band. To improve readability, we also fit a linear regression on the data and we also report the estimated slope on the graph whenever significantly different from zero (at a 95% confidence level).

The general picture that emerges is one where no relationship is in place between the variables, independently from both sector of activity and financial conditions. Indeed, with the only exception of Mid Risk Service firms, where a negative relationship is in place, but very weak ($\alpha = -0.013$) and of dubious significance (standard error of 0.004), the estimated slopes are never statistically different from zero, suggesting that firms are not able (or not willing) to translate their productive efficiency into sales. It is difficult to come out with a satisfactory justification for this finding, especially given the relative simplicity of the exercise we are performing. Without going too far with the interpretation, the lack of relationship between the two variables is at least in line with the above mentioned complexity of the issue: the processes generating quantifiable performances in production activity and market success are many and their relative importance unclear.

Next we proceed exploring the link between productivity and profitability. Here we are interested in uncovering whether and to what extent efficiency in organizing and carrying out production is translated into economic value for the firm. We repeat the previous exercise: for each sector and for each rating class, we divide the firms in equipopulated bins according to Labour Productivity and this time we compute the average ROS level inside each bin. Then, in Figure 14, we report average quantities together with the associated two standard error bands. Even if we cannot control for market power, nor, more generally, for other possible factors affecting pricing policies, what one should expect a priori would be to find a positive relation, as higher efficiency, allowing to operate at lower costs, should map into higher profitability. Visual inspection of the graphs, confirmed also by the estimation results, is in strong accordance with such a prediction.

In the Manufacturing industry, the overall result is the emergence of a clear positive relationship: firms that perform better in terms of productive efficiency are also those performing better in terms of profitability. A close look to the numbers on the axes and to the estimated slope coefficients helps evaluating the different patterns across the classes. On the one hand, as suggested by the similar values taken by the slopes, the extent of the relationship does not vary with the financial rating. On the other hand, rating classes are ranked in terms of average profitability in a way that is consistent with their ranking in productivity. Indeed, Low Risk firms operates at relatively higher levels of both ROS (mostly above 0.1) and Labor Productivity, while Mid Risk firms appear more concentrated around ROS levels below 0.1 and smaller values of Labour Productivity. Then, High Risk firms follow displaying the worst performances, with even lower Labor Productivity associated with negative values of ROS.

Manufacturing



Service

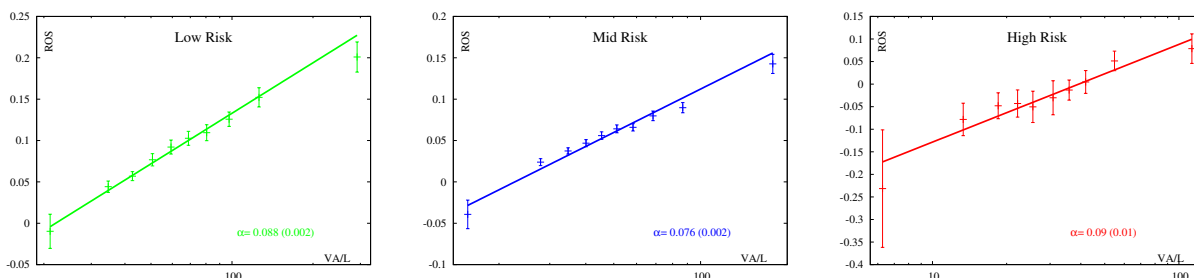


Figure 14: Profitability (ROS) as a function of Labor Productivity (VA/L) for the Manufacturing and Services sectors. Confidence intervals are reported as two standard errors (on each side). If the slope is significantly different from zero ($p < .05$) a linear fit is reported, otherwise the $y = 0$ axis is displayed.

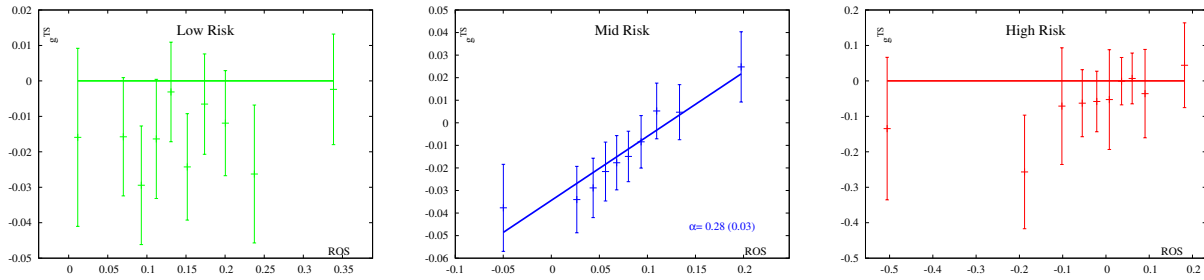
We also observe, however, an interesting phenomenon: at the top level of the productivity distribution, one finds High Risk firms which succeed in achieving profitability levels which are comparable with (or even higher than) those attained by firms in the other two classes.

The picture does not change when looking at Services. The slope coefficients are again positive and not very different across the classes, although they are generally smaller than the corresponding estimates for Manufacturing. The estimated intercepts are also smaller, meaning that, with respect to what we observed in the Manufacturing industry, all the classes operate at lower levels of ROS . Despite these differences, the ranking among the classes is preserved: Low Risk firms still achieve higher performances along both the dimensions considered, then Mid Risk and High Risk firms come in the order. Overall, the evidence is in broad agreement with simple economic reasoning. Profitability is indeed the outcome of firms' effort to perform economically viable operations by keeping costs relatively low and setting price relatively high. Efficiency in production is obviously of crucial help, especially in keeping costs low, and it is not surprising to observe that profitability increases with productivity.

As a final step we investigate the relationship between firm growth and profitability. We build bins of firms according to their ROS records and report in Figure 15 the average growth rate, g^{TS} , against the average profitability in each bin, once again together with two standard error bands. The result is extremely clear and robust at every level of aggregation: differential profitability does not seem to yield any differential ability (or propensity) to grow more. The estimation of a linear regression fully confirms this impression.

Summarizing, we documented a clear difficulty in translating productive efficiency into higher market shares. The preliminary analyses conducted suggest that this finding is es-

Manufacturing



Service

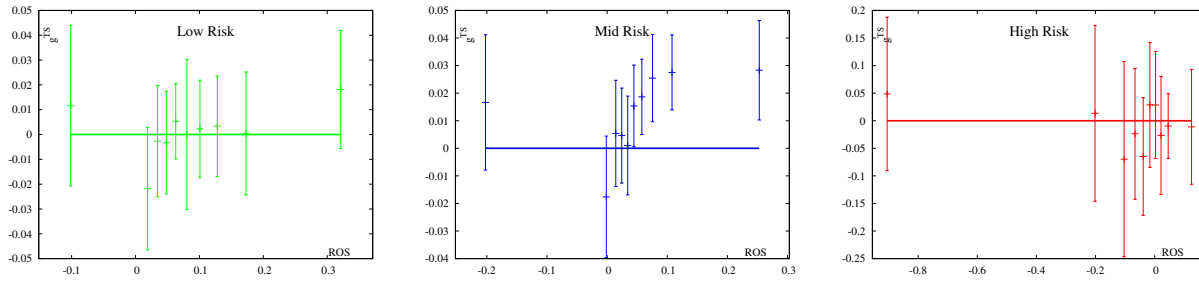


Figure 15: Average growth rate (g^{TS}) as a function of profitability (ROS) for the Manufacturing and Services sectors. Confidence intervals are reported as two standard errors (on each side). If the slope is significantly different from zero ($p < .05$) a linear fit is reported, otherwise the $y = 0$ axis is displayed.

essentially due to the inability (or the unwillingness), on the part of the firms, of translating profitability into market shares. Indeed, while higher productivity does map into higher profitability, this latter is not accompanied by higher growth. The results are robust across sector of activity and rating class.

References

- Ahn, S. ,2000, “Firm dynamics and Productivity Growth: A Review of Micro Evidence from OECD Countries”, *OECD Economics Department Working Paper* No. 297.
- Baily, M., E.J. Bartelsman and J.C. Haltiwanger, 1996, “Downsizing and Productivity Growth: Myth or Reality?”, *Small Business Economics*, **8**, 259-278.
- Bartelsman, E.J. and M. Doms, 2000, “Understanding productivity: Lessons from Longitudinal Microdata”, *Journal of Economic Literature*, **38**, 569-594.
- Bartelsman, E.J. and P.J. Dhrymes, 1998, “productivity Dynamics: U.S. Manufacturing Plants 1972-1986”, *Journal of Productivity Analysis*, **9**, 5-34.
- Bottazzi, G. and A. Secchi, 2003, “Common Properties and Sectoral Specificities in the Dynamics of U.S. Manufacturing Companies”, *Review of Industrial Organization* **23**, 217-232.
- Bottazzi, G. and A. Secchi, 2005a, “Growth and Diversification Patterns of the Worldwide Pharmaceutical Industry”, *Review of Industrial Organization* **26**, 195-216 .
- Bottazzi, G. and A. Secchi, 2005b, “Explaining the Distribution of Firms Growth Rates”, *The RAND Journal of Economics*, forthcoming.
- Bottazzi, G., E. Cefis, G. Dosi, 2002, “Corporate Growth and Industrial Structures: Some Evidence from the Italian Manufacturing Industry”, *Industrial and Corporate Change*, **11**, 705-723.
- Bottazzi, G., M. Grazzi and A. Secchi, 2005, ”Characterizing the Production Process: A Disaggregated Analysis of Italian Manufacturing Firms”, *Rivista di Politica Economica* **I-II**, 243-270.
- Bottazzi, G., M. Grazzi and A. Secchi, 2005, “Input output scaling relations in Italian manufacturing firms”, *Physica A*, **355**, 95-102.
- Bottazzi, G., A. Secchi and F. Tamagni, 2006, “Financial Fragility and Growth Dynamics of Italian Business Firms”, *LEM Working Papers* 2006/7, Sant’Anna School of Advanced Studies, Pisa, Italy.
- Chesher, A., 1979, “Testing the Law of Proportionate Effects”, *Journal of Industrial Economics* **27**, 403-411.
- Coad, A., 2005, “Testing the Principle of Growth of the Fitter: the Relationship between Profits and Firm growth”, *Department of Economics Working Papers*, 31/2005, Emory University, Atlanta, USA.
- Cubbin, J. and P.A. Geroski, 1987, “The convergence of profits in the long run: inter-firm and inter-industry comparisons”, *Journal of Industrial Economics* **35**, 427-442.
- DiNardo, J. and J.L. Tobias, 2001, “Nonparametric Density and Regression Estimation”, *Journal of Economic Perspectives*, **15**, 11-28.

- Dosi, G., 2005, "Statistical regularities in the Evolution of Industries. A Guide through some Evidence and Challenges for the Theory", *LEM Working Papers* 2005/17, Sant'Anna School of Advanced Studies, Pisa, Italy.
- Dosi, G. and M. Grazzi, 2006, "Technology as Problem-Solving Procedures and Technology as Input-Output Relations: Some Perspectives on the Theory of Production", *Industrial and Corporate Change*, **15**, 173-202.
- Foster, L., J. Haltiwanger and C.J. Krizan, 2001, "Aggregate Productivity Growth: Lessons from Microeconomic Evidence" in Dean, E., M. Harper and C. Hulten (Eds.), *New Developments in Productivity Analysis*. Chicago: University of Chicago Press.
- Foster, L., J. Haltiwanger and C. Syverson, 2005, "Reallocation, Firm Turnover, and Efficiency: selection on Productivity or profitability", *Center for Economic Studies Discussion Papers*, No. 11/2005, Bureau of Census, Washington, DC.
- Geroski, P.A., 1990, "Modelling persistent profitability", in Mueller, D.C. (Ed.), *The Dynamics of Company Profits: An International Comparison*. Cambridge: Cambridge University Press.
- Geroski, P.A., and A. Jacquemin, 1988, "The persistence of profits: a European comparison", *Economic Journal*, **98**, 375-389.
- Glen, J., K. Lee and A. Singh, 2001, "Persistence of profitability and competition in emerging markets", *Economics Letters*, **72**, 247-53.
- Glen, J., K. Lee and A. Singh, 2003, "Corporate Profitability and the Dynamics of Competition in Emerging Markets: a Time Series Analysis", *The Economic Journal*, **113**, F465-F484.
- Goddard, J.A. and J.O.S. Wilson, 1999, "The persistence of profits: a new empirical interpretation", *International Journal of Industrial Organization*, **17**, 663-687.
- Goddard, J.A., P. Molyneux and J.O.S. Wilson, 2004, "Dynamics of Growth and Profitability in Banking", *Journal of Money, Credit, and Banking*, **36**, 1069-1090.
- Griliches, Z. and J. Mairesse, 1995, "Production Functions: The Search for Identification", *NBER Working Papers Series*, No. 5067.
- Huber, P.J., 1967, "The behavior of maximum likelihood estimates under nonstandard conditions", *Proceedings of the Fifth Berkeley Mathematical Symposium on Mathematical Statistics and Probability*, **Vol. I**, 221-223.
- Huber, P.J., 1981, *Robust Statistics*. New York: John Wiley and Sons.
- Levinsohn, J., and A. Petrin, 2003, "Estimating Production Functions using Inputs to Control for Unobservables", *Review of Economic Studies* **70**, 317-34.
- White, H., 1980, "Some Heteroskedasticity Consistent Covariance Matrix Estimator with improved finite sample properties." *Journal of Econometrics* **29**, 305-325.
- Maruyama, N. H. Odagiri, 2002, "Does the Persistence of Profits Persist?: a Study of Company Profits in Japan, 1964-97", *International Journal of Industrial Organization*, **20**, 1513-1533.

- McGaham, A.M. and M. E. Porter, 1999, "The Persistence of Shocks to Profitability", *Review of Economics and Statistics*, **81**, 143-153.
- Mueller, D.C., 1977, "The persistence of profits above the norm", *Economica*, **44**, 369-380.
- Mueller, D.C., 1986, *Profits in the Long Run*. Cambridge: Cambridge University Press.
- Mueller, D.C. (Ed.), 1990, *The Dynamics of Company Profits: An International Comparison*. Cambridge: Cambridge University Press, Cambridge.
- Nelson, R.R., and S.G. Winter, 1982. *An Evolutionary Theory of Economic Change*. Cambridge, Mass: The Belknap Press of Harvard University Press.
- Olley, S.G., and A. Pakes, 1996, "The Dynamics of Productivity in the Telecommunications Equipment Industry" *Econometrica* **64**, 1263-1297.
- Schohl, F., 1990, "Persistence of profits in the long run: a critical extension of some recent findings" *International Journal of Industrial Organization*, **8**, 385-404.
- Silverman, B.W., 1981 *Density Estimation for Statistics and Data Analysis*. London: Chapman and Hall.
- Slade, M., 2004, "Competing Models of Firm Profitability", *International Journal of Industrial Organization*, **22**, 289-308.
- Subbotin, M.T., 1923, "On the Law of Frequency of Errors" *Matematicheskii Sbornik* **31**, 296-301.
- Tybout, J.R., 2000, "manufacturing Firms in Developing Countries: How ell Do They Do, and Why?", *Journal of Economic Literature*, **38**, 7-40.
- Waring, G.F., 1996, "Industry differences in the persistence of firm-specific returns", *American Economic Review*, **86**, 1253-1265.
- Winter, S.G, 2006, "Toward a neo-schumpeterian theory of the firm." *Industrial and Corporate Change*, **15**, 125-141.
- Wooldridge, J.M., 2000 *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: The MIT Press.