Corporate Growth and Industrial Structures: Some Evidence from the Italian Manufacturing Industry*

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Abstract

The work analyses the properties of corporate growth in a large longitudinal sample of Italian manufacturing firms. In particular, it focuses on the study of the statistical properties of growth rates and on the influence of proxies for relative efficiency upon relative growth. In line with Bottazzi et al. (2001), the emergence of "fat tails" in growth rates distribution and the idiosyncratic nature of autocorrelation coefficients confirm the existence of a structure in the growth process richer then the one normally assumed by the "Gibrat Law" hypothesis and suggest the presence of firm-specific drivers of growth. At the same time, one finds remarkable puzzles concerning the absence of any negative relationship between size and growth variance and only weak influences of relative efficiencies upon growth dynamics.

Key Words: Firm Size Distribution; Firm Growth; Gibrat Law; Fat Tails; Productivity; Market Selection.

JEL Classification: L11, D21, C14, O30

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1 Introduction

In this work we report preliminary results of an investigation on industrial dynamics based on a decade of micro longitudinal data from four Italian industries — pharmaceuticals, primary metals, machine tools and textile — chosen as representative of quite diverse production technologies and learning modes. Here we begin addressing two sets of issues concerning (i) the shape of the size distributions and their possible inter-sectoral differences, and (ii) the characteristics of growth dynamics.

A classic reference, when dealing with the statistical properties of firm growth, is the so-called "Law of Proportionate Effect" (or "Gibrat Law") (Gibrat, 1931) entailing process of stochastic growth uncorrelated with size and basically driven by several small idiosyncratic events. If $x_i(t)$ stands for the logarithm of firm i size[1] at time t, according to this Law its size at time $t+1$ reads[2]

$$x_i(t+1) = a + bx_i(t) + \epsilon_i(t) \tag{1}$$

where a is an industry-wide drift, b is an auto-regressive component and ϵ are random variables independent from x. Equation 1, under the restriction of $b = 1$, can be considered as a sort of "null hypothesis" regarding the firm dynamics. Note that it is also an hypothesis that makes evolutionary economists rather uncomfortable, in that it seems at odds both with several pieces of microeconomics evidence highlighting long-standing differences in technological and organizational competences across firms, and also with a notion of a competitive process systematically selecting within such population of heterogeneous firms[3].

Moreover, the overall evidence on "Gibrat Law" from the literature, often based on not-too-good data, is rather mixed and, often, the performed analysis simply amounts to testing the statistical acceptability of the $b = 1$ restriction via the estimation of a first order autoregressive process AR(1) on the whole panel data (for reviews and discussions see Dosi et al. (1995), Geroski (2000) and Sutton (1997)). As we argue at greater length in Dosi et al. (1995),

[1]Where size can be measured with respect to some "extensive" variable such as total sales, value added or employees. In the Gibrat literature the problem of what variables to choose has seldom been discussed and, when done, it has been mainly to affirm the irrelevance of such a choice (Stanley et al. (1997),among others). As we shall see below this might be a misleading assumption.

[2]For discussions, following the pioneering Ijiri and Simon (1977), cf., among others, Brock and Evans (1986), Boeri (1989), Sutton (1997), Geroski (2000), Dosi et al. (1995),Marsili (2001), Cefis et al. (2001).

[3]Incidentally note also that violations of Gibrat-type process of growth based on i.i.d. shocks are also implied by equilibrium models of industrial dynamics such as Jovanovic (1982) and Ericson and Pakes (1995): cf. Pakes and Ericson (1998)

Bottazzi et al. (2001); Bottazzi (2000) and Cefis et al. (2001) such an approach is likely to fall well short of the identification of the possible underlying structures in the growth process. An alternative, put forward in Bottazzi et al. (2001), involves testing for: **(a)** "fat tails" in the distribution of growth shocks with (relatively rare) "spurs of growth", **(b)** possible autocorrelations of growth rates over time and **(c)** firm-specificities in growth patterns which are persistent over time (as suggested by Cefis et al. (2001)). Such properties do indeed emerge in the case of world top pharmaceutical firms (Bottazzi et al. (2001) and Cefis et al. (2001)). However, an obvious issue regards the generality of such findings. Are the foregoing properties dependent upon the particular features of learning and competition of the drugs industry or, conversely, are they rather general characteristics of industrial dynamics? And, even if the latter hypothesis held true, to what extent are such characteristics influenced by industry-specific factors? We shall address these questions in the following.

Moreover, size as such might not be the best variables upon which to condition growth events. Rather, it is much more in tune with an evolutionary idea of heterogeneity *cum* market selection[4] to search for proxies of relative degrees of firm "competitiveness" and investigate their impact on firm growth profiles. This is what we shall also do below, using labor productivities as proxies for production efficiencies.

In Sec. 2 we briefly describe the database and the variables under scrutiny. Sec. 3 discusses the evidence on size distributions, the distribution of growth shocks and their possible autocorrelation. Sec. 4 considers the relationship between firm size and growth variances. In Sec. 5, we analyze relative labor productivities and their dynamics while in Sec. 6 we study their relationships with growth profiles.

2 The Database

This research draws upon the MICRO.1 databank developed by the Italian Statistical Office (ISTAT)[5]. MICRO.1 contains longitudinal data on a panel of several thousand Italian firms with employment of 20 units or more over around a decade, of which for statistical consistency we utilize the period 1989-96.

In this work we are exclusively interested in the process of *internal* growth, as opposed to the growth due to mergers, acquisitions and divestments. In order to control for the latter we

[4]Within a rapidly expanding evolutionary literature on industrial dynamics let us just mention three of the "seeding classics", namely Winter (1971), Nelson and Winter (1982) and Winter (1984).

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

build “super-firms” which account throughout the period for the union of the entities which undertake such changes. So, for example, if two firms merged at some time, we consider them merged throughout the whole period. Conversely, if a firm is spun off from another one, we “re-merge” them starting from the separation period.

Moreover, since the panel is open, due to entry, exit, fluctuations around the 20 employees threshold and variability in response rates we consider only the firms that are present both at the beginning and at the end of our window of observation.

Firms are classified according to their sector of principal activity[6]. For the analysis that follows, as already mentioned, we have chosen pharmaceuticals[7],primary metals[8], machine tools[9] and textiles[10] which can be reasonably taken as representative of the Pavitt's taxonomic classes identified as “science-based”, “scale-intensive”, “specialized supply” and “supplier dominated”, respectively Pavitt (1984). Here we consider Pavitt's categories to represent a suggestive attempt to classify different industrial sectors according to the diverse modes of generation and exploitation of novel opportunities of product and process innovation (cf. also Dosi (1988) and Marsili (2001)). In turn, diverse regimes of technological learning might well influence growth dynamics.

The statistical variables we consider here are the total number of employees $L_i(t)$, sales $S_i(t)$ and value added $V_i(t)$ of “super-firm” i at time $t \in [1, \ldots, 8]$, together with labor productivity defined as $\Pi_i(t) = V_i(t)/L_i(t)$.

It is often convenient to analyze the normalized logarithm of those variables. For instance, regarding the number of employees we define

$$l_i(t) = \log(L_i(t)) - < \log(L_i(t)) >_i \tag{2}$$

where $< . >_i$ stands for the average over all the firms at a given time. Analogously, we define “rescaled” log sales $s_i(t)$ and log value added $v_i(t)$. These variables are characterized by stationary distributions[11] and allow us to treat the growth process on these normalized quantities as a stationary one. Let us denote the various growth rates as

$$g_i^x(t) = x_i(t+1) - x_i(t) \tag{3}$$

[6]The Italian ATECO.3 classification closely matches the ISIC one.

[7]Ateco.3: 24.4 Pharmaceuticals; 97 observations

[8]Ateco.3: 27.1 Ferrous and Non-ferrous Metals; 67 observations

[9]Ateco.3: 29.4 Machine Tools; 114 observations

[10]Ateco.3: 17.2 Textiles; 171 observations

[11]We have checked the stationarity hypothesis using Kolmogorov-Smirnov tests and we find robust evidence supporting it: the significance is always greater than .96.

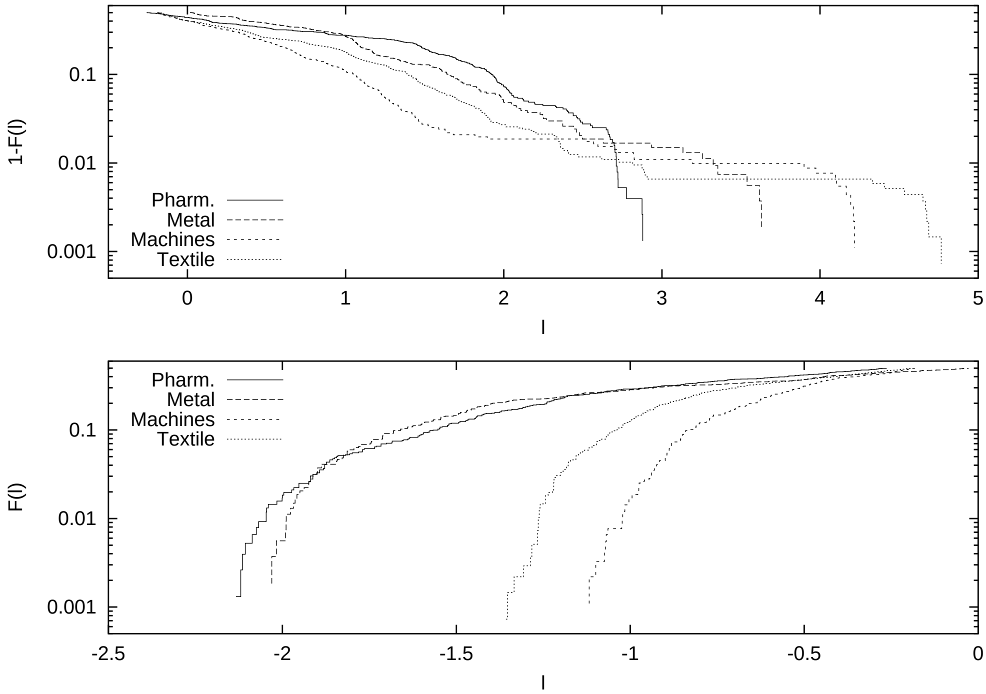

Figure 1: Upper (top) and lower (bottom) half of the size distribution function in term of number of employees in the four sectors (computed using the whole database time horizon).

where x takes the values l,s and v respectively for the number of employees, sales and value added.

Note that through this "rescaling" procedure one washes away common trend effects due to both inflationary dynamics and real (i.e. constant price) expansion/contraction of the industry as a whole (including those captured by a in eq. 1).

3 Size Distributions and Corporate Growth

Size distributions

Due to the relative low number of observations, it is safer to plot the distribution function rather then the probability densities. It is also handy to refer to a "symmetric transformation" of such a distribution function. In what follows (for clarity purposes) we will use the "symmetrized" version of the distribution function $F(x)$ defined according to

$$F_s(x) = \begin{cases} F(x) & F(x) < .5 \\ 1 - F(x) & F(x) > .5 \end{cases} \tag{4}$$

(Under this convention, in what follows we drop by convenience the subscript s.)

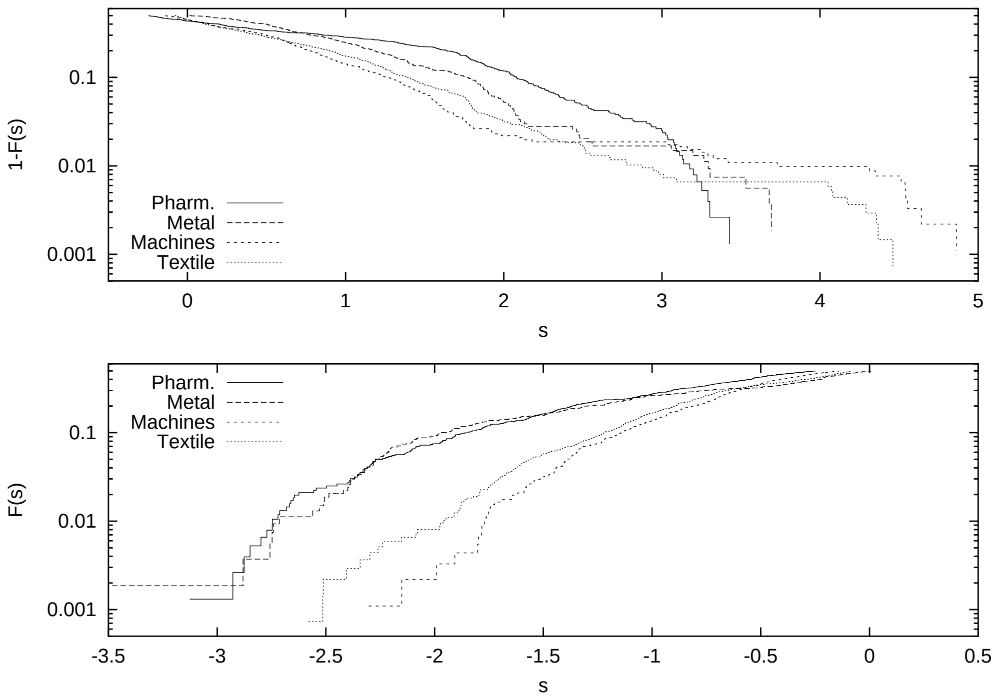

Figure 2: Upper (top) and lower (bottom) half of the size distribution function in term of sales in the four sectors (computed using the whole database time horizon).

In Fig. 1 and Fig. 2 we show the upper and lower tails of the ("symmetrized") probability density. They display important difference both in tails and supports. The latter variable suggest different "spreads" of sizes in different industries. Concerning the former, notice that higher tails means more concentrated industries, i.e. the share of the total industry possessed by the top fraction of firm population is higher when the probability density is asymptotically higher.

First, notice the striking intersectoral differences in our proxy for concentration, well in tune with an established "stylized fact" from industrial economics. Interestingly, the representatives of "science based" and "scale intensive" sectors (pharmaceuticals and primary metals, respectively) are more concentrated and display smaller support, i.e. relatively lower size asymmetries. The converse hold for "specialized suppliers" and "suppliers dominated" sectors (machine tools and textiles).

Second, the upper tails also show (with the exception of pharmaceuticals) some large gap which can be intuitively interpreted as a sort of "barrier" separating different segments of the industry, i.e. a core part from a fringe one. Indeed the large width of these gaps, compared to the average size of growth shocks (see also below), implies that the large majority of micro-dynamics develops separately inside the different segments, with rare events of crossing.

Third, the lower tails appear to be more homogeneous across sectors, but we are also less confident about making any inference on a tail "artificially bent" by a sampling threshold, further burdened by proportionally more frequent missing observations due to rather noisy response rates by smaller firms.

Fourth, the slope of the upper tails for all sectors tend to fall for the middle-to-high size range so that the curve takes a convex shape (this is in fact analogous to what happens on Italian data in Pareto fit to the top firms[12]) and the power-like behavior seems to be interrupted by a sudden decrease.

Incidentally notice also some of the further interpretative questions inspired by this evidence: among them, to what extent are these patterns influenced by the institutional specificities of the Italian case?, and, conversely, how robust are inter-sectoral differences which hold for the same sectors across different countries?

Growth dynamics

In order to characterize the growth process, let us begin by checking if any relationship between size and growth is present in our data. Interestingly, both the growth means and growth variances do *not* display any relationship with size[13]. This circumstantial evidence for the weaker form of the "Law of Proportionate Effect", prescribing the lack of any relationship between growth and size, appears at work here.

However, consider as a benchmark for the dynamics a "stronger" Gibrat hypothesis, whereby growth shocks should be well described by a lognormal distribution[14] and compare it with the actual distribution of g^l and g^s shown in Fig. 3 and Fig. 4, respectively.

The plots clearly show how a lognormal distribution dramatically underestimates the "fatness" of the observed tails.

Let us try then to fit the data using a more fat-tailed distribution. In order to do that we use the Subbotin family of distributions (Subbotin, 1923) with density of the form[15].

[12]cf. Dosi et al. (2000)

[13]The lack of relationship concerning growth means is a robust result which has been found many times elsewhere (cf. the evidence discussed in Sutton (1997) and Geroski (2000)) (see also Sec. 4). Conversely, the presence of a negative relationship between size and growth variances which constitutes a quite typical feature of industrial data (cfr. the discussion in Bottazzi (2000)), is not displayed by our data.

[14]This is indeed a straightforward conjecture, under the Central Limit Theorem, once the idea of growth as a sequence of random shocks is accepted on every time scale.

[15]This in turn generalizes on a similar procedure used by Stanley et al. (1997) where a Laplace distribution is used. The relevance of such a generalization can be checked by looking at the fitted β exponents that are constantly lower then unity.

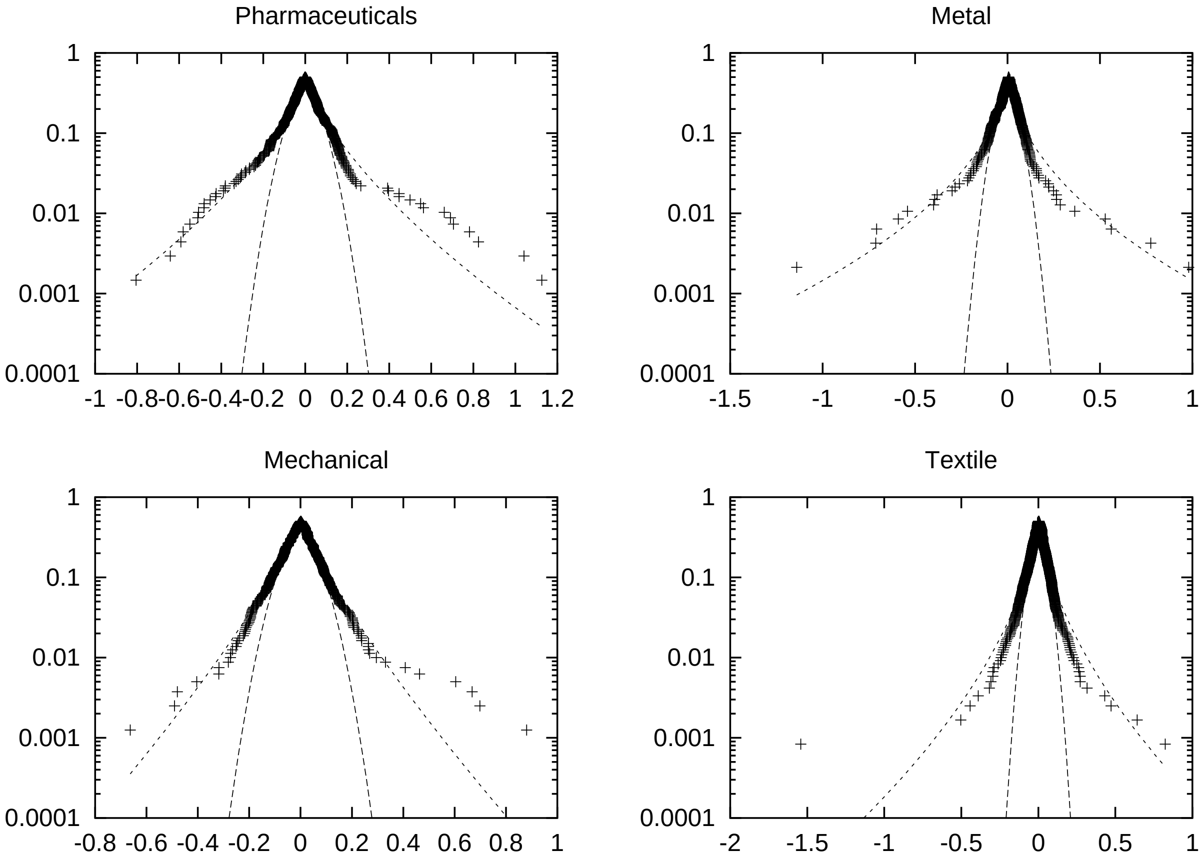

Figure 3: Probability densities for the (log) labor growth g^l in the four sectors. Broken lines show fits for a normal distribution (lower one) and a Subbotin distribution (upper one). (For the parameters of the latter see Tab. 1)

$$f(x) = \frac{1}{2}\frac{\beta\,\alpha^{1/\beta}}{\Gamma(1/\beta)}\, e^{-\alpha\,|x|^{\beta}} \tag{5}$$

Here $\Gamma(x)$ is the Gamma function and β represents a "shape parameter" shaping the distribution tails: for $\beta < 2$ the distribution is leptokurtic and is platikurtic for $\beta > 2$. The lower is β, the fatter are the tails. The "scale" parameter α describes the central width of the distribution. The $2l$-th central moment of the Subbotin distribution reads

$$m_{2l} = \alpha^{\frac{-2l}{\beta}}\,\frac{\Gamma((2l+1)/\beta)}{\Gamma(1/\beta)} \tag{6}$$

implying that the rescaled central moments (such as the kurtosis) do not depend on the parameter α. For $\beta = 2$ this distribution reduces to a Gaussian and for $\beta = 1$ to a symmetric exponential, i.e. Laplace, distribution.

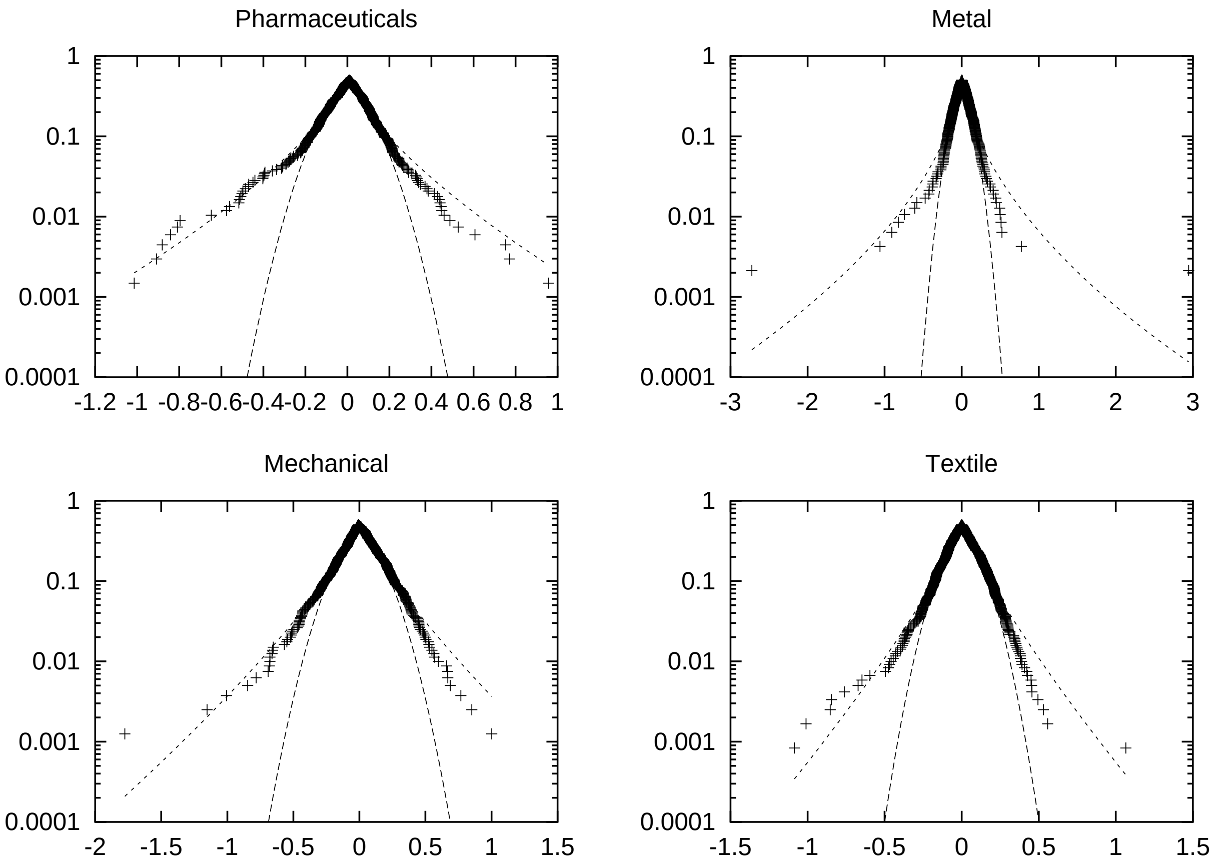

Figure 4: Probability densities for the (log) sales growth g^s in the four sectors. Again a normal (lower) and a Subbotin exponential (upper) fits are also shown. (For the parameter of the latter see Tab. 2)

To fit observed data we use the associated probability distribution function:

$$F(x) = \begin{cases} \frac{1}{2}\left(1 - P(1/\beta, \alpha|x|^\beta)\right) & x < 0 \\ \frac{1}{2}\left(1 + P(1/\beta, \alpha x^\beta)\right) & x > 0 \end{cases} \tag{7}$$

where $P(a, x)$ stands for the incomplete Gamma function:

$$P(a, x) = \frac{1}{\Gamma(a)} \int_0^x e^{-t}\, t^{a-1}\, dt \tag{8}$$

In general the distribution (7) provides a good description of the observed frequencies on a wide range of values. Interestingly, the major drawback comes from a remarkable asymmetry of the growth distribution between positive and negative parts, both for the sales and the employees variables, at least in some of our sectors.

In Tab. 1 and Tab. 2 we report the result of a least square fitting procedure of (7) on the observed frequencies.

	Pharm.	Metal	Mech.	Textile
α	8.27	9.03	10.99	10.37
β	0.58	0.39	0.77	0.49
σ^2	0.0234	0.02461	0.01161	0.01039

Table 1: Parameters from least squares fitting of the g^l distribution with a Subbotin function.

	Pharm.	Metal	Mech.	Textile
α	6.83	6.62	5.7	7.55
β	0.62	0.46	0.73	0.76
σ^2	0.0429	0.0743	0.0658	0.0307

Table 2: Parameters from least squares fitting of the g^s distribution with a Subbotin function.

First, our data display rather different values of β across sectors, revealing also diverse degrees of indivisibility of investments: a good illustration are primary metals where new plants, with an associated "normal" size of the labor force, are plausibly rather "lumpy" (cf. Tab. 1). (Conversely, capacity utilization and thus sales may adjust more smoothly). Together our data show impressively different "scales" for the growth shocks (as captured by parameter α).

Second, one observes different degrees of "impactedness" of the tails of the distributions between employment vs. sales growth within the same sectors. Begin by noticing that growth appears to be in general more "lumpy" in terms of employees rather than sales, as one can easily see comparing the β values of Tab. 1 with those of Tab. 2. It is impossible to asses, on the grounds of our data, the extent to which such a "lumpiness" is due to institutional features of the Italian labor market. Certainly, however, there is a strong technological component, where metal and textiles stand out as the sector with fatter tails (expecially on the positive side).

Third, concerning the asymmetries between positive and negative shocks, note that *positive* tails tend to be relatively fatter in terms of employments while *negative* tails are fatter in terms of sales (suggesting the possibility of rather large "competitive disasters").

	Pharm.	Metal	Mech.	Textile
mean	0.0789	0.093	0.095	0.123
σ	0.320	0.327	0.306	0.351
significance (P val.)	0.0085	0.00034	9.511010^{-05}	4.6710^{-08}

Table 3: Mean and standard deviation of the autocorrelations coefficients distribution for labor growth for the four sectors. The significance of the Kolmogorov-Smirnov comparison test between the observed distributions and the distributions obtained with randomly resampled (bootstrapped) growth shocks is also shown.

	Pharm.	Metal	Mech.	Textile
mean	0.085	-0.016	-0.066	0.124
σ	0.327	0.284	0.305	0.351
significance (P val.)	0.0042	0.815	0.029	4.6710^{-8}

Table 4: Mean and standard deviation of the autocorrelations coefficients distribution for sales growth for the four sectors. (cf. Tab. 3)

Autocorrelation

Another major question concerns the presence of autocorrelation in the growth dynamics of firms. Hence, we compute for each variable (employees, sales and value added), the histogram of the autocorrelation coefficients for all the firms in a given sector. The mean of this distribution represents the sampled autocorrelation computed using all the firm of the panel. Under the assumption that different firm histories were to represent different realizations of the same random process, this should indeed be the best estimate of the autocorrelation in the overall growth process. In fact, as reported in Tab. 3 and Tab. 4, the means are in general close to zero and, even when their differences from zero are marginally significant, their small values (around .01) cannot *prima facie* suggest any remarkable, persistent difference in firms growth profiles, at least over the relatively short time horizon characterizing our database.

However, the assumption of "identity" amongst firms turns out to be rather questionable. In order to check to what extent different firms dynamics can be treated as the outcome of the same underlying process, one may compare the observed frequencies distributions, shown in Fig. 5 and Fig. 6 for the labor and sales variables respectively, with the ones obtained from a dataset made of "artificial firms histories" that satisfy this identity requirement by

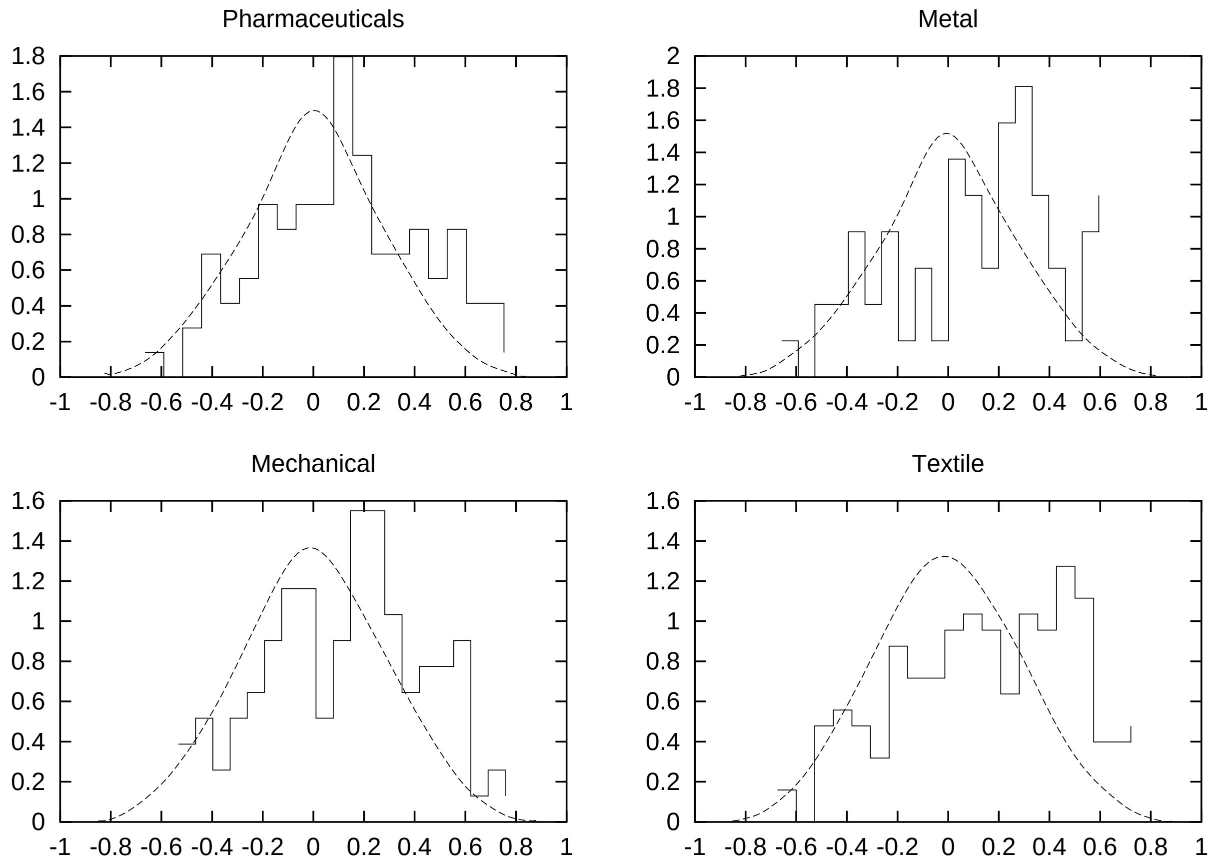

Figure 5: Observed frequency for the autocorrelation coefficient of g^l growth (steps function) and the associated density distribution computed using 10000 bootstrapped time series (dotted line). See Tab. 3 for the mean values and the results of a Kolmogorov-Smirnov comparison between observed and bootstrapped distributions.

construction. These histories can be obtained by a "bootstrap sampling", i.e. by randomly extracting "growth rates" from the set of all the observed growth rates.

If one then compute again the autocorrelation distribution on this "artificial dataset" , a different shape is obtained (cfr. Fig. 5 and Fig. 6). The difference between the two is revealed by performing a Kolmogorov-Smirnov test comparison between the "artificial" and the observed distributions, and by looking at the obtained significance of p-values (i.e. the probability the observed differences between the distributions might be simply a matter of chance). As can be seen in Tab. 3 and Tab. 4, the p-value is in many cases so low to lead to a clear rejection of the "identity" hypothesis between the growth processes of different firms.

Here, again, the evidence is circumstantial, but it is surprisingly well in tune with the findings from Cefis et al. (2001) hinting at powerful idiosyncratic patterns of growth. The

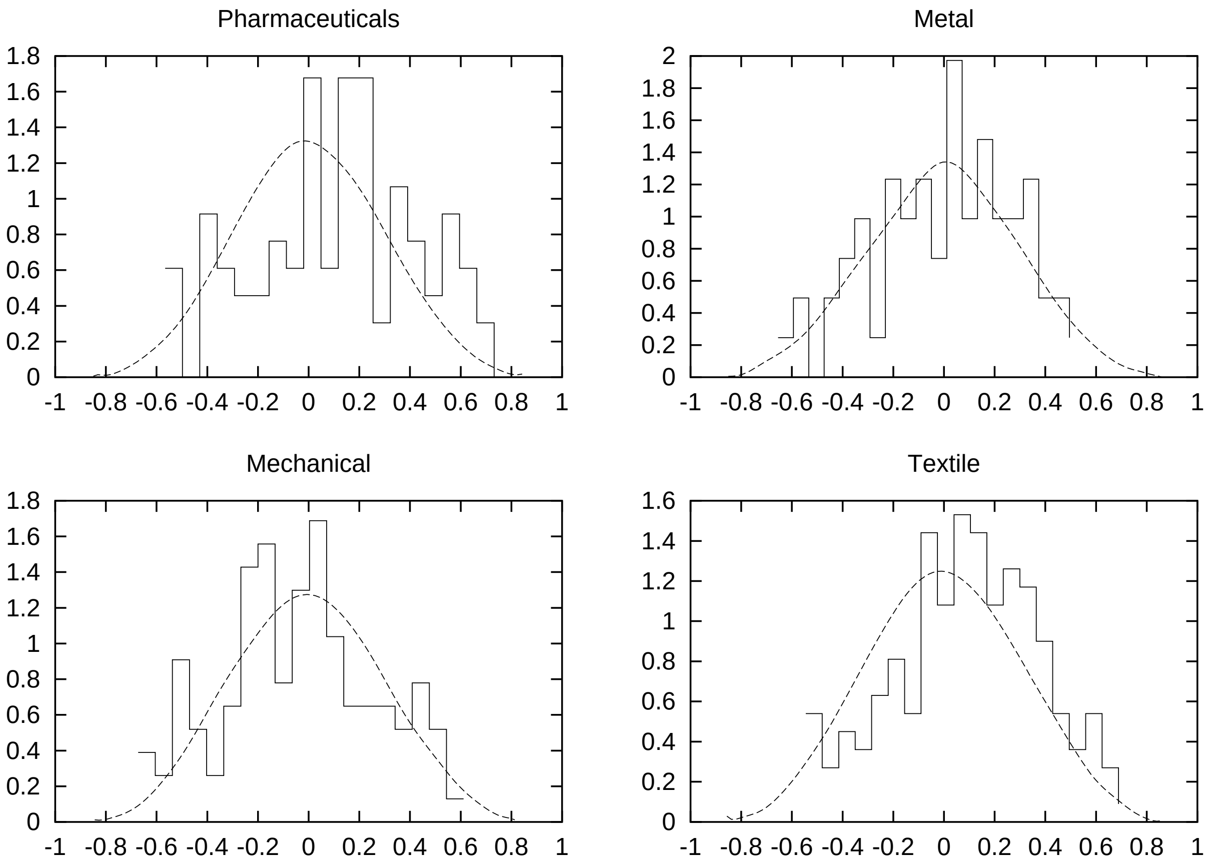

Figure 6: Observed frequency for the autocorrelation coefficient of g^s growth (steps function) and the associated density distribution computed using 10000 bootstrapped time series (dotted line). See Tab. 4 for the mean values and the results of a Kolmogorov-Smirnov comparison between observed and bootstrapped distributions.

promising conjecture is that growth dynamics are persistently asymmetric across firms, that firm-specific processes display a long memory, and that, together, we are still at a preliminary stage in identifying the underlying (technological and organizational) conditioning factors.

4 Corporate Sizes and Growth Variances

As already mentioned, a rather robust evidence suggests a variance of growth rates falling with corporate size (cf., among others, Evans (1987a), Evans (1987b) and Hall (1987)). Our data on a subset of Italian industries covering a rather comprehensive sample of firms with more than 20 employees conflict with such a common wisdom. As shown in Fig. 7 for the

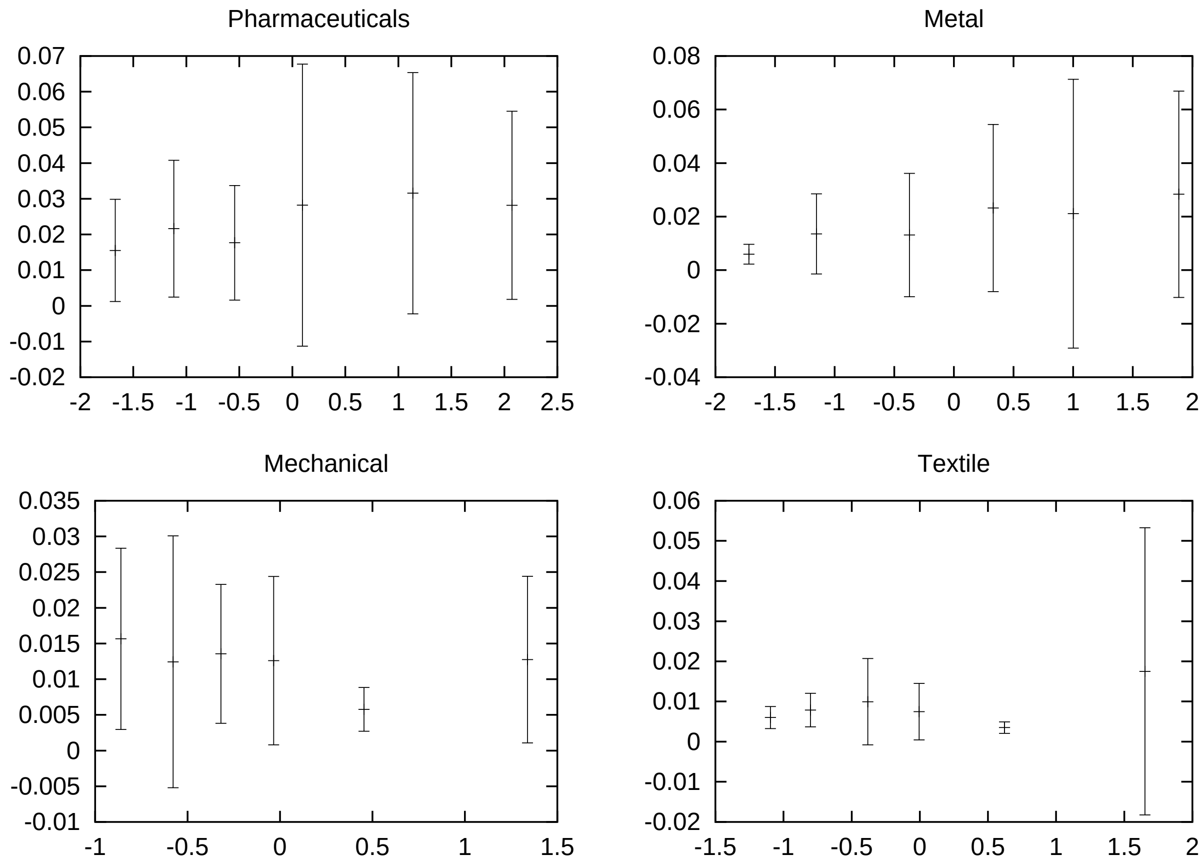

Figure 7: The average rate of growth of the number of employees g^l for equipopulated bins of firms partitioned according to the number of employees l. The error bars correspond to 3 standard deviations.

number of employees no such pattern appears[16].

In Bottazzi (2000) one proposes an explanation of the negative variance-size relationship grounded into diversification patterns (for a similar interpretation on the American manufacturing industry cf. Stanley et al. (1997)).

In brief, Bottazzi (2000) and Bottazzi et al. (2001) show that the number of markets in which a firm diversifies bears a (less than proportional) relation with size and than the underlying dynamics is a (plausibly, competence-driven) branching process. In turn diversification across (uncorrelated) markets fully explains the observed coefficients of the negative relation between growth variance and size.

[16]The analysis using sales gives very similar results.

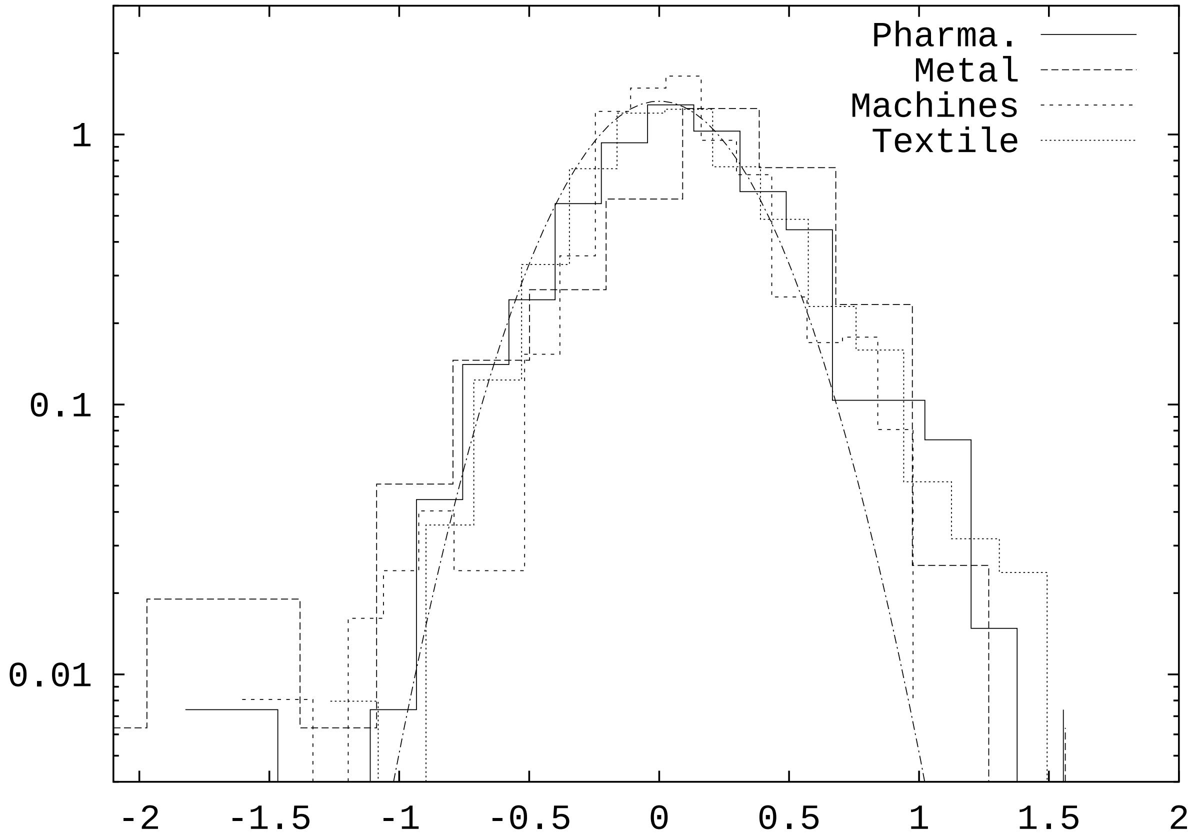

Figure 8: Probability densities of the productivity π for the four sectors under analysis (the normal distribution is plotted as a guide for the eyes) .

5 Labor Productivities

Recall the definition given in Section 2 of Π (the Value Added per Employee) and of the rescaled (log) variable π, as such a proxy for relative labor productivities. Figure 8 presents the distributions of such quantities by sector. (Given the stationarity of the distributions over the considered time period, we pool all yearly observations together.)

First note that an implication of the observed stationarity is the lack of any reduction in the distributions variances over time, suggesting a persistence in the micro-heterogeneity, prominently shown by the wideness of the distribution supports. Indeed, this strongly corroborates a central evolutionary conjecture on the quite inertial reproduction over time of *diverse capabilities* and related diverse performances, favored also by the general difficulties of ("boundedly rational") economic agents in learning new technological and organizational practices, and even in identifying the notionally most promising ones.

Second, again, fat tails reveal the systematic presence of a relative large number of "outper-

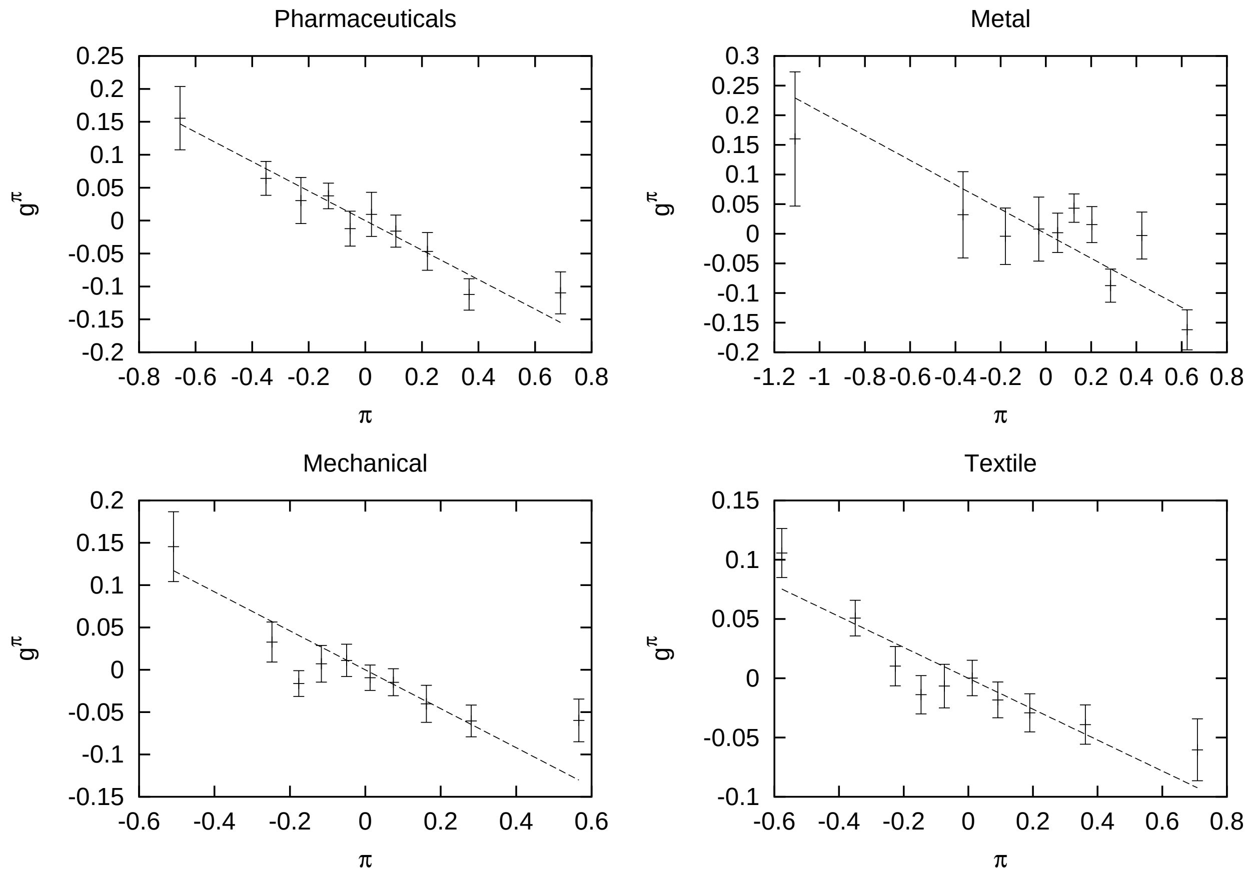

Figure 9: Regression of the productivity growth g^π on the average productivity π. The data are distributed according to the latter in 10 equipopulated bins. The regression parameters are reported in Tab. 5.

formers" and "underperformers" — as compared to a normal distribution benchmark. Moreover, as suggested by the positive skewness of the distributions, the observations concerning the highest productivities are further away from the distributions averages.

Given such distributions, what are the dynamics of productivity over time?

In Fig. 9 we show the average productivity growth for different productivity bins[17]. An inverse relationship emerges, where more productive firms are on average doomed to see their relative productivities decreasing relatively to the industry average the following year. This is of course consistent with some process of *learning* and *imitation* amongst firms which leads to fast *capabilities diffusion* over the industry: "catching up" abilities of the technological followers appears to wash away relatively quickly positions of (temporary) leadership in production efficiency. However, no systematic reversion to the mean tendency emerges: distributions of

[17] "Bin" stands for a quantile in the distribution of the population in the variable at hand

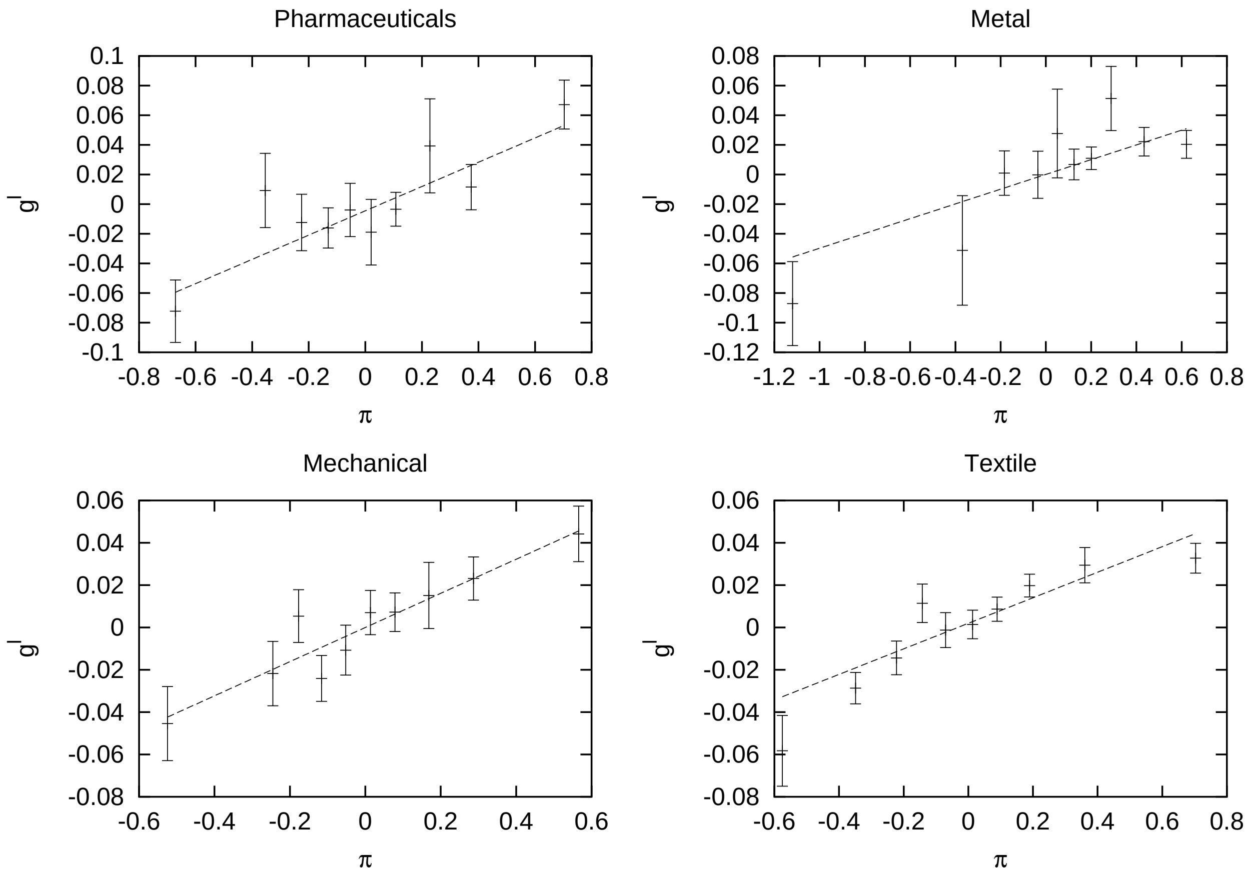

Figure 10: Regression of the employees growth g^l against (relative) productivity π. The data are distributed according to the latter in 10 equipopulated bins. The regression parameters are reported in Tab. 6.

relative productivities are stable over time. This basic evidence is corroborated by statistics (not shown here) concerning growth rates of productivity over the whole period against initial relative productivities: mild evidence of some catching-up tendency is there, but unable to yield an increasing uniformity amongst firms.

6 Relative Efficiency and Corporate Growth

A fundamental hypothesis of evolutionary theories is that differential levels of "competitiveness" (or "fitness") systematically affect relative growth rates of micro entities.

Let us plot employees and sales growth for different bins over the π distribution. Results for the employees case are shown in Fig. 10. Here, a clear positive relationship appears, supported also by exercise of linear regression of the employment growth vs. relative productivity, whose

	Pharm.	Metal	Mech.	Textile
r	-.013	-0.23	-0.2	-.22
σ_r	.015	0.023	0.031	.025
r/σ_r %	12	10	15	11

Table 5: The slope r and the asymptotic standard error as obtained with an OLS linear regression of the productivity growth vs. actual productivity.

	Pharm.	Metal	Mech.	Textile
r	.081	.049	.08	.06
σ_r	.015	.012	.012	.01
r/σ_r %	18	25	15	16

Table 6: The slope r and the asymptotic standard error as obtained with an OLS linear regression of the employees growth vs. labor productivity.

estimated coefficients are reported in Tab. 6. The positive relationship appears quite robust and, noteworthy, rather homogenous for the different sectors.

Such a dynamic is well in tune with a "replicator-type" process of market selection whereby, in probability, firms with above-average productivity tend to expand and that below the average tend to shrink. However, in our data, we observe that this relationship disappears when considering firm growth as measured in terms of sales or Value Added rather then employees[18]. Even more puzzling, such a relation tends to disappear when considering long-run relationships (i.e. growth measured on larger time spans) between relative productivities on the one hand, and any growth indicator (e.g. employment, value added or sales), on the other.

Finally, a prominent phenomenon highlighted by all our evidence is the role of *outliers*, i.e. by the presence of few remarkable *outperformers* and few remarkable *underperformers* which systematically appear and have non-negligible impact on the sector dynamics. This applies to cumulative productivity growth, to systematic growth in proxies of size (labor and value added) and also to the relationship between far-from-average productivity growth and far-from-average growth proxies. One is tempted here to think that most "near-average" differences in our admittedly very noisy proxy for "competitiveness" pick up also many factors of non-prices competition, and, together, many roughly *neutral drifts* in technologies, orga-

[18]This is indeed a puzzle that we intend to explore in future works

nizational arrangements and strategies. Together, few "hopeful monsters" - in the biological analogy - stand out above the noise involved in our accounting proxies and drive systemic changes in productivity and market shares. At the opposite extreme, market selection seems to operate quite gently, if at all, *vis--vis* most "near-average" agents. Its role, it seems, is mainly to cut out the very worse performers.

7 Conclusions

As already mentioned, this work is just a preliminary study within a wider search of the statistical regularities of industrial dynamics. As such it suggest both relatively robust insights into the nature of the underlying evolutionary process and also some intriguing challenges. In these conclusions let us mainly focus on the latter.

Start from the puzzling property of our data, which, in tune with a lot of the evidence reviewed in Geroski (2000), lack any strong autocorrelation in the growth process.

This is particularly puzzling since also in our data one finds abundant evidence of systematic heterogeneity across firms. First, as discussed above, we find at least circumstantial evidence of differences across firms in the generating processes of growth shocks. Second, and even more important, our data display striking persistent differences across firms in production efficiencies.

Why shouldn't these asymmetries in efficiency be reflected in more systematic selection processes autocorrelated over time? Part of the answer might rest in the differences in the time scales at which productivity shocks arrive vis-à-vis the time scale at which market adjustments take place. After all, we have in the real world asynchronous processes of adjustments in production technologies, prices and market shares which might be badly reflected by an "artificial" sampling over one-year time periods (This is also akin the hypothesis put forward by Geroski (2000)).

However, we are not convinced that this is by any means the whole story. A lot of evidence from the literature suggests that profits tends to be asymmetrically distributed and that such asymmetries are persistent over time. In future works we intend to check whether these properties apply also to our data and whether they are systematically correlated with asymmetries in efficiency. If that were the case, one would have to draw also far-reaching implications regarding the patterns of competition.

First, one might be forced to conclude that asymmetric efficiencies do not translate so much in systematic "replicator-type" dynamics in the relative sizes of output but primarily in differential abilities to generate profits (and possibly affect relative sizes in the longer term only through the impact of profitability upon investment).

Second, an equally challenging implication of our evidence is that selection dynamics are primarily driven by outliers.

While qualitative evidence suggests that "near-average" performances map into "near-average" growth, some striking outliers systematically appear on both efficiency and growth indicators. It might well be that selection operates mostly in the long run, and mostly through the upper and lower distribution tails.

Relatedly, the dynamics of both the efficiency distributions and the revealed growth rates distributions suggest symmetry breaking system behavior whereby outliers are the main drivers of long term changes.

Another puzzle regards the evidence stemming form our data of any lack of relationship between growth variance and size - contrary to a lot of previous evidence from the literature (Sutton, 1997), and contrary also to our findings on the international pharmaceutical industry (Bottazzi, 2000; Bottazzi et al., 2001). The lack of such a relationship in our Italian data might be interpreted on the ground of different, possibly complementary, phenomena.

First, it might well be that diversification plays a relatively weaker role in Italian firms. Second, it could be the even when diversification occurs, it affects lines of business whose demand profiles tend to be highly correlated. Third, it could be a statistical artifact stemming from the ways "firms" are defined, mainly for fiscal reason[19]. Come as it may, the determinants of the variance in growth profiles is yet another challenging issue ahead.

All together, the foregoing evidence adds elements to the interpretation of the patterns of industrial evolution, with their generic invariances and their inter-sectoral differences. One of the apparent invariances regard the structure of the growth process, with "fat-tailed" distributions of shocks - confirming the findings of Bottazzi et al. (2001). At the same time, the parametrizations of such distribution do depend on the specific sectors. Concerning the underlying determinants of growth itself, the lack of robust correlations between proxies of efficiency and firms' growth continue to remain a puzzle for evolutionary analysts. Perhaps, one should identify better proxies for the "competitiveness" of each firms; or, maybe, markets do not work too well as selection devices at least on the time scale of our observations; or, the determinants of growth have highly idiosyncratic components that can only be captured

[19]Note that this could well be the case if the diversification of business groups has mostly occurred through the formation of formally separate legal entities (cf. the discussions, unfortunately in Italian, in Balconi (1996) and Barca (1997)).

through detailed firm by firm investigations. Come as it may, the issue stands as a major challenge facing evolutionary theory.

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