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Sectoral Specificities in the Dynamics of U.S. Manufacturing Firms

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Abstract

The size distribution and growth rates dynamics of U.S. manufacturing firms have been extensively studied by many authors. In this paper, using the COMPUSTAT database, we extend the analysis to disaggregated data, studying 15 industrial sectors. We find that among the stylized facts presented in literature concerning the whole industry, some survive and can be considered valid for each single sector while some disappear, suggesting that their emergence was purely due to aggregation effects. The degree of heterogeneity in the behavior of the different sectors hints at a richer economic structure and, consequently, stresses the loss of information implied in limiting the investigations at an aggregate level.

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1 Introduction

The statistical analysis of the firm size and its dynamics constitutes one of the traditional problems in the Industrial Organization literature. Early investigations were conducted over

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datasets at a high level of aggregation, typically including large firms operating in very different sectors. For instance Hart and Prais (1956) study the distribution of the whole U.K. manufacturing industry while Simon and Bonini (1958) explore the size distribution of the top manufacturing firms of the U.S. economy, across all the sectors. These investigations were primarily focused on the analysis of size distribution and the characterization of firms growth dynamics in terms of autoregressive stochastic processes (in an enormous body of contributions see for instance Dunne et al. (1988); Evans (1987); Hall (1987)).

More recent contributions (Stanley et al., 1996; Amaral et al., 1997) extend these studies to the analysis of the growth rates distribution and its dependence on company size. In particular they show that the growth rates distribution of U.S. firms aggregated over all the manufacturing sectors displays a tent-like shape that can be represented by a Laplace (symmetric exponential) distribution. They also identify a robust scaling relation between the variance of growth rates and the firm size.

A common shortcoming in these studies resides in the possibility that considering such aggregate data can introduce statistical regularities that are only the result of aggregation (e.g. via Central Limit Theorem) and can conceal the true characteristics of the dynamics of business firms that are active in specific sectors. From an economic point of view, indeed, one could argue that the sectoral specificities in the nature of production and the different demand structures in markets for different goods make the "pooling" of firms operating in different industrial sectors an extremely dangerous exercise and the conclusion so drawn devoid of practical utility, if not meaningless. The existence of these strong sectoral specificities in the growth dynamics of manufacturing firms was recognized quite early. For instance Hymer and Pashigian (1962), analyzing disaggregated data, find a high heterogeneity in firms size distribution across different sectors. They conclude that it is quite unclear whether any "stylized fact" concerning the size distribution actually exists.

The present work follows in part the spirit of this last contribution and compares aggregated and disaggregated (sectoral) data. We perform a set of parametric and non parametric statistical analysis of firms growth dynamics using the COMPUSTAT database and considering the whole U.S. manufacturing industry. Succinctly, we will study the stationarity and shape of firms size distribution, the autoregressive structure of the growth dynamics and the statistical properties of growth rate density. Our analysis on aggregated data largely confirms the previous findings. We then repeat these analysis at the disaggregated level, considering one industrial sector at the time. With this simple exercise we are able to investigate two relevant questions. First, which are the statistical features characterizing the aggregate dynamic that survive the disaggregation process, i.e. that can be considered at least roughly valid at sectoral level? Second, which is the degree of heterogeneity in the results of the anlyses across different sectors and to what extent the sectoral features that do not appear in the aggregate statistics differ among them?

The remainder of this paper is organized as follows. In Sec. 2 a short description of the data source is provided. In Sec. 3 and Sec. 4 the analysis on the aggregated database and on each sector separately are respectively performed. In Sec. 5 we tentatively put forward some possible interpretation of the findings, before concluding in Sec. 6.

2 Data Description

All the analyses we perform in this paper are based on the well known COMPUSTAT databank; in particular we consider US publicly traded firms in the manufacturing sector (SIC codes ranging from 2000 to 3999) in the time window 1982-2001. To elude the problem of low numbers of firms in the first years and at the same time to fully exploit the database we build two different panels: one balanced and one unbalanced. In the first we shorten the relevant time range to 1993-2001 ending up with a sample of 1025 firms (cfr. Tab. 1 for details). The unbalanced panel is built in order to maximize the number of firms considered over the whole period and consists of more than three thousands firms, (cfr. again Tab. 1). The balanced panel will be used for the parametric analysis of the autoregressive structures while we use the unbalanced version for the non parametric analysis to satisfy the higher requirements of these techniques in terms of number of observations. Since we use non parametric techniques essentially for graphic and qualitative investigations this switch from balanced to unbalanced datasets remains a meaningful procedure.

3 Aggregate properties

In this section we perform some simple statistical analyses on firm size distribution and firm dynamics considering data pooled over all the industrial sectors. As a measure of size we use the firm total sales. The analysis is developed along three steps: first, the statistical description

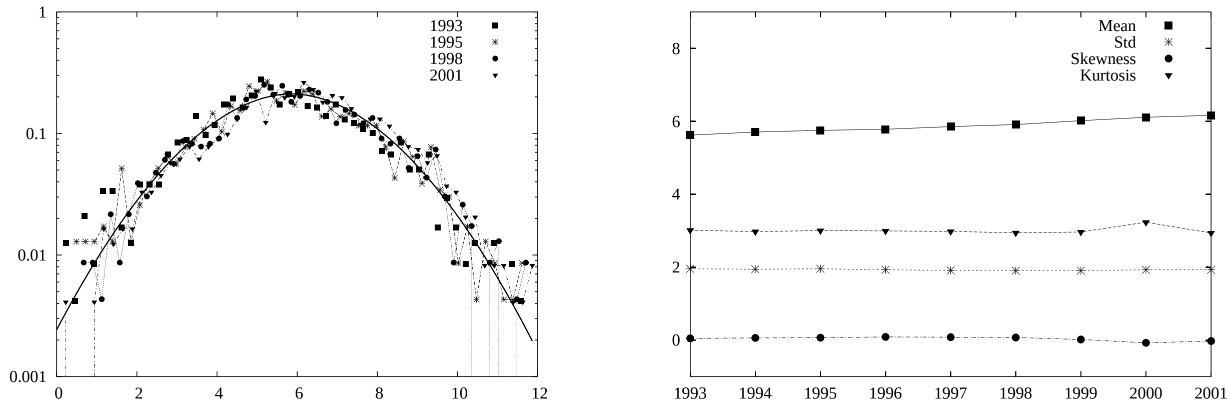

Figure 1: **Left:** Empirical probability densities of (log) sales $\log(S_i)$ for 4 different years together with a log normal desnity fitted pooling the 9 years together. **Right:** The time evolution over the whole range 1993-2001 of the first four moments of the size distribution.

of firms size distribution, second the characterization of the autoregressive structure of the growth process and, last, the analysis of the variance of growth rates and of their empirical density. These three steps will be repeated in the next Section for each sector separately.

Size Distribution

We start with the analysis of stationarity of the size distribution. In the left-side of Fig. 1 we plot, in a log-scale, the probability density of the log of firm size, $\log(S)$, in 4 different years 1993, 1995, 1996 and 2001. Visual inspection of these densities reveals two main features. First, the size distributions disclose strong stationarity. This finding is also confirmed by the right-hand side of Fig. 1 where the time evolution of the first four moments of the distribution is plotted over the whole range 1993-2001. Leaving aside a slightly upward trend in the mean all the other three moments seem vey much stable over time. Second, the empirical probability densities seem very well approximated by a log normal density, as can be judged by the log normal fit reported in Fig. 1.

Autoregressive structure

We want to analize the autoregressive structure of the firm size time series estimating an AR(1) process on $\log(S_i)$. For this purpose we will use the balanced panel and in order to eliminate the aforementioned trend in the average size we consider the normalized (log) size

$$s_i(t) = \log(S_i(t)) - \frac{1}{N}\sum_{i=1}^{N}\log(S_i(t)) \tag{1}$$

subtracting from the (log) size of each firm the average (log) size of all the firms. Here N stands for the total number of firms in the balanced panel.

On these observations we estimate the AR(1) model

$$s_i(t) = \phi\, s_i(t-1) + \epsilon_i(t) \tag{2}$$

where we do not introduce any firm specific term for the (log) size average. We interpret different firms as different realizations of the same stochastic process. We use a *Four-Stages Instrumental Variables Estimator* (Ljung (1987) pag. 403) in order to get around problems due to possible color and heteroskedasticity in the error terms[1]. This estimation procedure returns an approximately optimal set of instruments. The estimated coefficient is found to be $\phi = 0.9576 \pm 0.005147$ and our analysis confirms the existence of a unit root in the growth process. Notice that this result is well in accordance with many previous studies (cfr. among many others Hart and Prais (1956); Hymer and Pashigian (1962); Mansfield (1962); Simon and Bonini (1958)) on similar databases.

The unit-root nature of the size process implies that the firm growth process can be described by a geometric Brownian motion. It is interesting then to investigate the possible autoregressive structure of the first differenced process. We consider the (log) growth rates defined as the first difference of (log) size according to

$$g_i(t) = s_i(t+1) - s_i(t) \quad . \tag{3}$$

Notice that from (1) the distribution of the g's is by construction centered around 0 for any t.

We estimate

$$g_i(t) = \phi_g\, g_i(t-1) + \epsilon_i(t) \tag{4}$$

using the same multistep procedure used for equation (2). We obtain an estimated autoregressive coefficient $\phi^g = 0.0621 \pm 0.0140$, significantly different from zero even if very small (the variance of g being $\sim .24$). We also estimate an AR(2) process on the same observations

$$g_i(t) = \phi_1^g\, g_i(t-1) + \phi_2^g\, g_i(t-2) + \epsilon_i(t) \tag{5}$$

[1]Indeed, as will be clear below, the process under analysis does show both heteroskedasticity and color in the error structure.

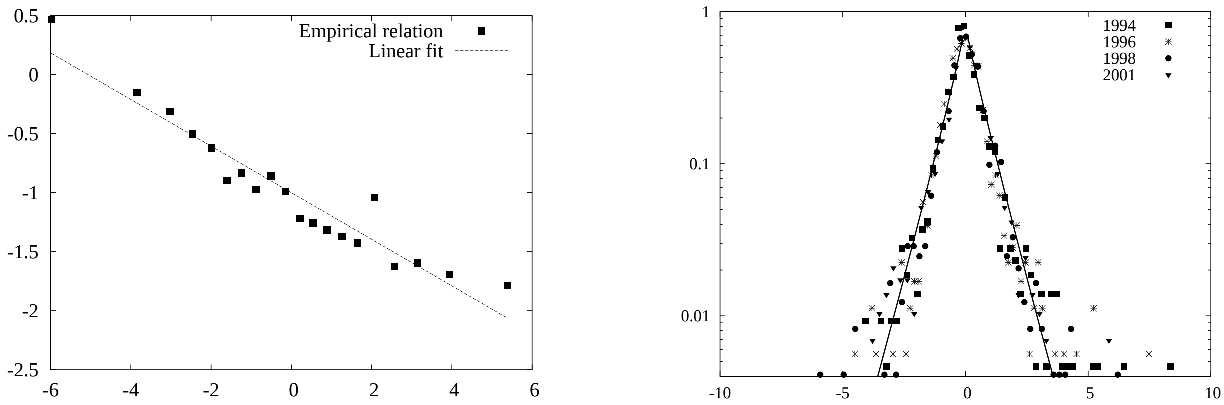

Figure 2: **Left:** The log of the standard deviation of the 1 year growth rates as a function of s. The power behavior $\sigma(g|S) \sim S^{\beta}$ with β equal to -0.19 ± 0.03 is also shown. **Right:** Empirical densities of rescaled growth rates in 4 different years together with a Laplacian fit.

obtaining a two-lag coefficient ϕ_2^g not significantly different from zero and an identical one lag coefficient $\phi_1^g \sim \phi_g$. We conclude that the AR(1) model completely accounts for the autoregressive structure in data.

Growth density and variance-size relation

From the early investigations of Hymer and Pashigian (1962) it has been suggested that the variance of business firms growth rates can decrease when their size increases; in particular Amaral et al. (1997) show that the standard deviation of firms growth rates $g_i(t)$ scales with size according to a Power Law $\sigma(g|S) \sim S^{\beta}$ with β approximately equal to -0.20 ± 0.03. Considering the time frame 1993-2001 we split the $s_i(t)$'s in 20 bins (quantiles) and compute the standard deviation of the associated growth rates $g_i(t)$ in each bin. We fit the linear relation

$$\log(\sigma(g|s)) = \alpha + \beta\, s \tag{6}$$

of the standard deviation on the average bin size and we find an exponent $\beta = -0.19 \pm 0.01$ that is strikingly similar to the one found by Amaral et al. (1997)[2]. In Fig. 2 we report the sample standard deviation for each bin vs. the average bin size. The linear fit provides a good description of the variance-size relation. Notice that we also performed the same exercise using the average growth rate instead of the standard deviation, but we did not find any relationship

[2] In Bottazzi et al. (2001) an analogous investigation has been conducted over the worldwide pharmaceutical industry where a value of $\beta = 0.20 \pm 0.02$ was found

with the firms size. Moreover, no robust relation was observed also for the higher moments of the distribution.

Since the dependence of the growth rates statistics on the size of the firm is completely described by the variance-size relation one can use (6) to define rescaled growth rates according to

$$\hat{g}_i(t) = g_i(t) / \left(\alpha\, e^{\beta\, s_i(t)}\right) \tag{7}$$

which are distributed with unit variance. In this way one obtains growth shocks whose statistics does not depend on the size of the firm they affected and it is then possible to pool together growth rates coming from firms in different size bins.

According to Stanley et al. (1996) the density of $\hat{g}$'s should display a characteristic tent shape that can be described using a Laplace (symmetric exponential) functional form:

$$f_{\mathrm{L}}(x; \mu, a) = \frac{1}{2a} e^{-\frac{|x-\mu|}{a}} \quad . \tag{8}$$

We plot the probability density of $\hat{g}$ for 4 different years in Fig. 2 together with the Laplace fit obtained using all the 9 years of data pooled together. As can be seen, the Stanley et al. (1996) result seems largely confirmed as the Laplace density well describes the observations. To quantify this agreement we follow a parametric approach and we consider the Subbotin family of distributions (Subbotin, 1923), already used in Bottazzi et al. (2002), that contains the Laplace density as a special case. This family is defined by 3 parameters: a positioning parameter μ, a scale parameter a and a shape parameter b. Its functional form reads:

$$f_{\mathrm{S}}(x) = \frac{1}{2ab^{1/b}\Gamma(1/b+1)}\; e^{-\frac{1}{b}\left|\frac{x-\mu}{a}\right|^b} \tag{9}$$

where $\Gamma(x)$ is the Gamma function. The lower is the shape parameter b, the fatter are the density tails. For $b < 2$ the density is leptokurtic and is platikurtic for $b > 2$. It is immediate to check that for $b = 2$ this density reduces to a Gaussian and for $b = 1$ to a Laplace.

We estimate the b parameter maximizing the likelihood of observed data. Notice that even if (9) is a three parameters family of densities its estimation on the $\hat{g}$'s is a one parameter estimation since μ is set to 0 by the normalization in (1) and the relationship between a and b is fixed by the rescaling procedure in (7) that imposes a unit variance. We find an estimated value of $b = 1.06$ which is really close to the theoretical Laplace value of 1.

To summarize, we found that the firms size distribution is stationary and characterized by a lognormal shape, confirming the results in Stanley et al. (1995). We showed that the growth

Sic code	Sector	# of Firms (bal.-unbal.)	Average size	Std of size	Skewness	Kurtosis
20	Food and kindred products	61-169	5.74	2.54	-0.28	-0.18
23	Apparel and other textile products	23-72	5.34	1.88	-0.96	2.33
26	Paper and allied products	37-80	6.16	2.21	-1.46	4.39
27	Printing and publishing	47-106	5.27	2.24	-0.89	0.75
28	Chemicals and allied products	128-646	3.35	3.33	-0.015	-0.56
29	Petroleum and coal products	30-54	7.81	3.07	-1.35	2.17
30	Rubber and miscellaneous plastics products	34-96	4.71	2.11	-0.52	1.26
32	Stone, clay, glass, and concrete products	21-46	5.21	2.17	-0.56	-0.09
33	Primary metal industries	51-122	5.99	2.05	-1.30	3.29
34	Fabricated metal products	45-98	4.78	1.99	-0.37	0.48
35	Industrial machinery and equipment	148-494	4.25	2.57	-0.19	0.65
36	Electrical and electronic equipment	144-611	4.07	2.31	0.20	0.89
37	Transportation equipment	57-157	6.14	2.87	-0.14	-0.16
38	Instruments and related products	95-484	3.09	2.41	-0.05	0.56
39	Miscellaneous manufacturing industries	24-89	4.09	1.92	-0.66	1.75
–	Whole industry (balanced panel)	1025	5.87	1.93	0.03	0.00

Table 1: Summary table of the 15 sectors under analysis. The estimated b parameters together with the exponent β of the scaling relation $\sigma(g) \sim S^{\beta}$ are reported.

process posseses a unit root and that the standard deviation of growth rates declines with size according to a Power law. The $g_i(t)$ dynamics is characterized by a very small autoregressive coefficient and the growth rates, once they are rescaled according to the proper variance/size relation, display a characteristic Laplace shape.

4 Sectoral analyses

The analyses run in the previous Section considered data aggregated across the whole manufacturing industry.

In the present Section we perform exactly the same statistical investigations but at a sectoral level, looking at the firms size distribution and at the growth dynamics sector by sector. In this way we can check to what extent the findings of the previous Section survive at a more disaggregated level.

We consider total sales of U.S. manufacturing firms disaggregated up to a 2-digit level

(SIC codes range from 20 to 39) in the time frame 1982-2001. For statistical reliability we restrict our analysis to the sectors with more than 21 firms: under this constraint the number of 2-digit sectors is reduced from 19 to 15.

Analogously to what done in the whole industry, for each sector we build a balanced panel and an unbalanced one. The 3-rd column of Table 1 reports for each sector the number of firms in the balanced panel and the maximum number of firms present at the same time in the unbalanced panel. In the 2-nd column a brief description of the sector activity is provided.

Size distribution

Similarly to what done in Section 3 we use the total sales as a definition of firms' size. Table 1 reports the first four moments of the size distributions for all the fifteen sectors analyzed.

From this table it is clear that the degree of heterogeneity in size distribution for the different sectors is rather high. For instance, the average and the standard deviation of (log) size range respectively from 3.09 to 7.81 and from 1.88 to 3.33. It is also apparent, from the fourth and the fifth column of Table 1, that remarkable sectoral specificities are present in the degree of symmetry and in the weight of tails of the sectoral size distributions. To give visual hints of these sectoral specificities in size distributions we present in the left panels of Fig. 3, Fig. 4 and Fig. 5 the case of three different sectors (Food and kindred products, Chemicals and allied products and Industrial machinery and equipment) chosen because both numerous and diverse. Beside the food sector, which displays approximately a lognormal size distribution, we observe in the Machinery and Chemicals sectors respectively left and right skewed distributions with high probability of presence of bimodality.

Autoregressive structure

Let $S_{i,j}(t)$ represent the sales of the i-th firm, belonging to the j-th sector, at time t. Here $j \in \{1, \ldots, 15\}$ and if N_j is the number of firms in the j-th sector then $i \in \{1, \ldots, N_j\}$. We define the normalized sectoral (log) sales as:

$$s_{ij}(t) = \log(S_{ij}(t)) - \frac{1}{N_j} \sum_{i=1}^{N_j} \log(S_{ij}(t)) \tag{10}$$

subtracting from the (log) size of each firm the average (log) size of all the firms operating in the same sector. Applying the same methodology used in Section 3 we estimate the model

$$s_{ij}(t) = \phi_j \, s_{ij}(t-1) + \epsilon_{ij}(t) \tag{11}$$

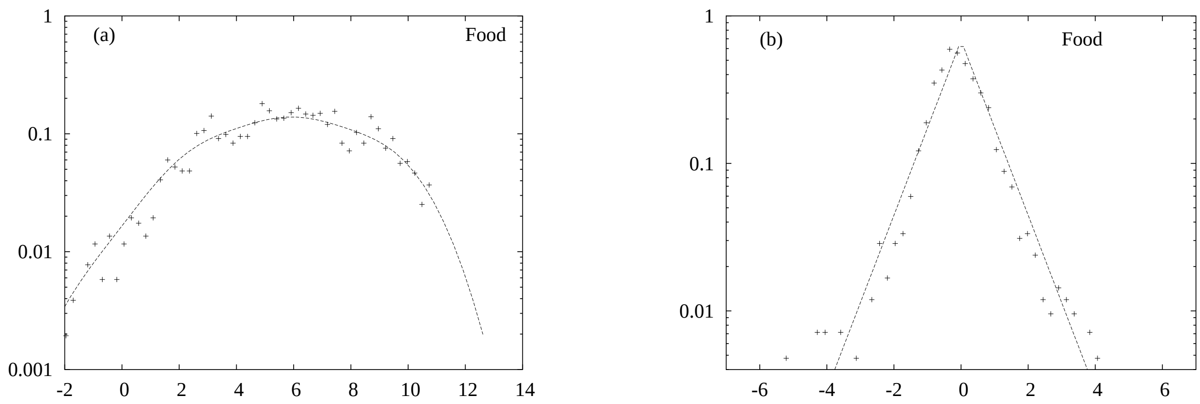

Figure 3: Binned probability density and kernel density estimation of **(a)** firm size and **(b)** growth rates for the Food sector.

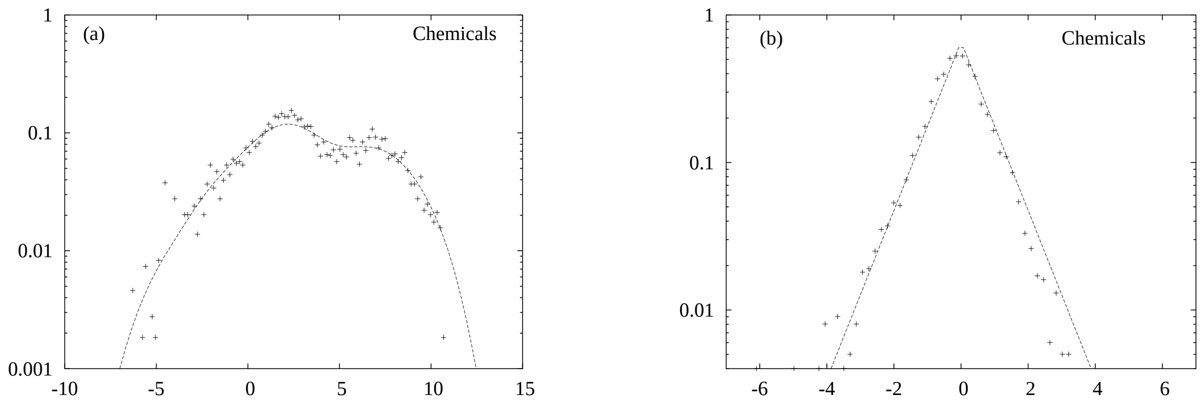

Figure 4: Binned probability density and kernel density estimation of **(a)** firm size and **(b)** growth rates for the Chemicals sector.

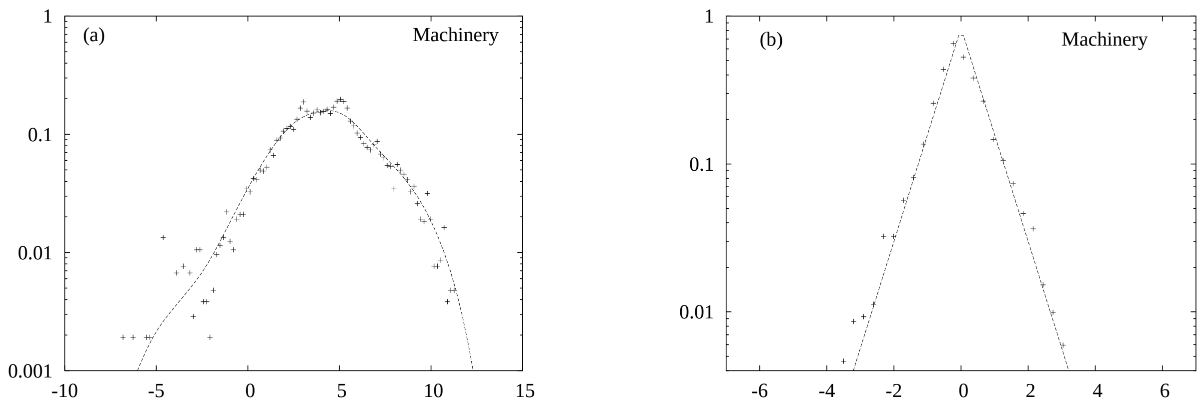

Figure 5: Binned probability density and kernel density estimation of **(a)** firm size and **(b)** growth rates for the Machinery sector.

Sic code	Sector	AR(1) levels	AR(1) differences	Estimated b	Scale Exponent
20	Food and kindred products	0.97 ±0.02	-0.08 ±0.05	1.08	-0.159 ± 0.018
23	Apparel and other textile products	0.97 ±0.03	0.18 ±0.08	1.05	-0.201 ±0.035
26	Paper and allied products	0.99 ±0.02	0.03 ±0.06	1.06	-0.171 ±0.024
27	Printing and publishing	0.96 ±0.02	-0.12 ±0.07	0.95	-0.188 ±0.026
28	Chemicals and allied products	0.95 ±0.01	0.07 ±0.04	1.02	-0.203 ±0.012
29	Petroleum and coal products	0.96 ±0.03	-0.20 ±0.07	1.21	-0.138 ±0.021
30	Rubber and miscellaneous plastics products	0.97 ±0.03	-0.16 ±0.07	0.87	-0.214 ±0.033
32	Stone, clay, glass, and concrete products	0.93 ±0.04	0.16 ±0.12	1.13	-0.148 ±0.21
33	Primary metal industries	0.88 ±0.03	-0.04 ±0.05	1.09	-0.217 ±0.028
34	Fabricated metal products	0.96 ±0.02	-0.06 ±0.06	0.85	-0.184 ±0.030
35	Industrial machinery and equipment	0.96 ±0.01	0.17 ±0.03	1.00	-0.196 ±0.019
36	Electrical and electronic equipment	0.98 ±0.01	0.05 ±0.04	0.80	-0.146 ±0.026
37	Transportation equipment	0.96 ±0.02	0.06 ±0.05	0.93	-0.149 ±0.019
38	Instruments and related products	0.92 ±0.02	0.02 ±0.04	1.06	-0.193 ±0.020
39	Miscellaneous manufacturing industries	0.90 ±0.04	-0.20 ±0.09	1.02	-0.193 ±0.029

Table 2: Summary table of the 15 sectors under analysis. The estimated b parameters together with the exponent β of the scaling relation $\sigma(g) \sim S^{\beta}$ are reported.

and we report the results in the first column of Tab. 2. In this case we observe a substantial homogeneity in the estimated AR coefficients in different sectors: they are all significant and very close to 1. We conclude that also at sectoral level the firm growth process is well described by a geometric Brownian motion.

We then consider the (log) growth rates defined according to

$$g_{ij}(t) = s_{ij}(t+1) - s_{ij}(t) \tag{12}$$

and we estimate an AR(1) model

$$g_{ij}(t) = \phi_g \, g_{ij}(t-1) + \epsilon_{ij}(t) \quad . \tag{13}$$

The results for the different sectors are reported in the second column of Tab. 2 and display a moderate degree of sectoral heterogeneity. Most of the sectors do not show any AR structure in growth rates (coefficients in sectors like Food and kindred products, Fabricated metals products and some others are not significantly different from 0), other present mild positive autoregressive coefficients (for instance Industrial machinery and equipment) while in some

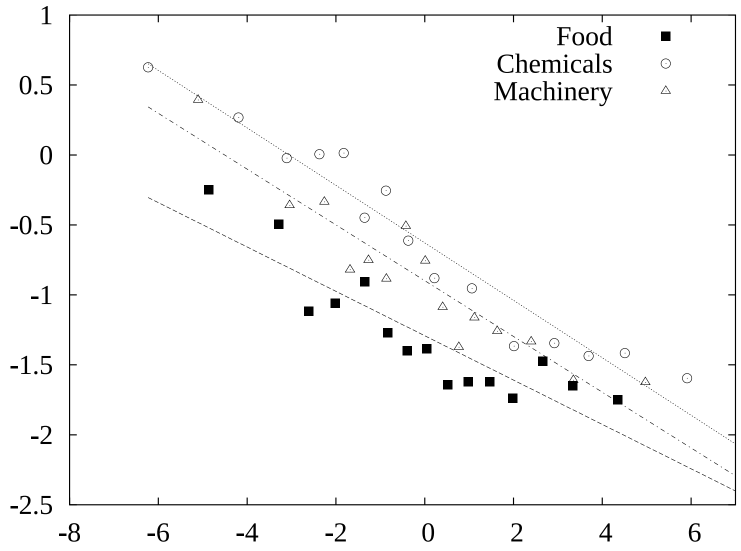

Figure 6: Dtandard deviation of growth rates for different size bins vs. average (log) size in the bins together with a linear fit. The Food sector (SIC 20), the Chemicals sector (SIC 28) and the Industrial Machinery sector (SIC 35) are shown.

other cases it is possible to observe mild negative autoregressive coefficients (for instance Petroleum and coal products and Rubber and miscellaneous plastic products).

Growth rates distribution and variance-size relation

We repeat at the sectoral level the same analysis performed above concerning the relation between the central moments of the growth rates and the size of firms. The result is analogous to the aggregate case, and only the variance of growth seems to depend on firm size. We fit (6) on 20 size bins for each sector separately. The results are reported in the last column of Tab. 2. In Fig. 4 we report as an example the bin scatter plot and the linear fit for three sectors.

The scaling coefficient ranges from the value $-.138$ for Petroleum and Coal product (SIC 29) to the value $-.217$ for Primary metal (SIC 33). The variation is noticeable even if, in the majority of cases, the distance from the aggregate value of $-.2$ is not large.

Exactly with the same procedure presented in (7) we are able to define for each sector the rescaled growth rates $\hat{g}_{ij}(t)$. In the right-hand panels of Fig. 3, Fig. 4 and Fig. 5 three examples of the $\hat{g}_{ij}(t)$ density are reported. The symmetric exponential fits describe with rather high accuracy the observations. Using the Subbotin family of densities in (9) we can obtain, via maximum likelihood estimation, a value for b relative to each sector. The results are reported in Tab. 2 and they are all very close to the value 1 indicating a Laplace density.

5 Possible Interpretations

The results of Sec. 3 and Sec. 4 show that among the different analysis performed, some give essentially the same result at aggregate and disaggregate level, while others, on the contrary, show a clear sectoral nature. An essential account of the aggregate/disaggregate robustness and of the degree of heterogeneity found, at sectoral level, for the various analysis is provided in Tab. 3.

In the group of results surviving disaggregation we find the stationarity of the size and growth rate distributions, the unit-root nature of the growth process, the dependence between variance of growth and firm size and the shape of the growth rates density. Notice that the similarity of these results at aggregate and disaggregate level also implies their similarity across all the sectors under study. This suggests that their nature has to do with some fundamental property of the economic dynamics and of the firms behavior. While for some of these findings the generality has long been recognized, like in the case of the unit root nature of firms growth typically referred as the Gibrat hypothesis (Gibrat, 1931), for other findings only recently an explanation has been proposed. In Bottazzi and Secchi (2003a,b) the tent-shape of firms growth rates density is explained as an emerging feature due to the existence of an underlying positive-feedback effect in the growth of firms, while in Bottazzi (2001) the relationship between growth rates variance and firm size has been explained as a diversification effect, i.e. as a relation between firm size and the number of submarkets in which the firm operates. Both these explanations do in fact rely on quite general assumptions that can be plausibly considered valid across all the U.S. manufacturing sectors. The existence of these effects in all the sectors constitute an argument in favor of these simple models.

The sectoral specificities are particularly strong in the firms size distribution and in the autoregressive nature of the growth process. In particular, it is interesting to notice the high heterogeneity of firms size distributions as opposed to the homogeneity of growth rates distributions. A possible explanation of this impressive evidence can be found in the same nature of the "stochastic description" of firms dynamics. Suppose, indeed, that the growth dynamics of business firms can be described, to the most part, by a stochastic model, except

	sectoral specific	sectoral heterogeneity
stationarity of size distribution	no	no
shape of firms size density	yes	high
AR structure in size levels	no	no
AR structure in growth rates	yes	moderate
growth rates variance vs. size	no	low
tent shape of growth rates density	no	low

Table 3: Comparison between the results of the aggregate and disaggregate level of analysis. The first column reports for which analysis the disaggregated level gives different findings. The second column reports the degree of heterogeneity that has been found across the sectors concerning this particular analysis.

from events that have nothing to do with the "generic" economic behavior, including, for instance, earthquakes or the discovery of balance sheet accounting frauds. If these events are, as it is the case, rare and of large magnitude, they can in fact permanently modify the shape of the size distribution. On the other hand, their impact on the growth rate distribution remains small and proportional to their sheer number. These argument suggests that the growth rates structure, being less affected by "historical" events, can carry more relevant information concerning the nature of the underlying economic process.

6 Conclusions and Outlook

The parallel statistical investigation of the firm growth dynamics at aggregate and at sectoral level allowed us to identify which properties are present in both level of analysis and which properties, on the other hand, disappear under the aggregation or disaggregation procedure. At the sectoral level, our analysis reveal the presence of extremely robust properties, like the tent-like shape of the growth rates density, together with properties of a more heterogeneous nature, like the firms size probability density.

We provided tentative explanations for the existence of robust characteristics across sectors. Essentially, we suggested that these characteristics can be explained with simple models, whose parsimonious requirements are so generically satisfied that they can be considered a good first approximation to many different industries. This, of course, is not intended as the end of the story, but just as a suggestion of which facts and which directions can be considered more relevant in, first, designing and, second, comparing micro-founded models of industry evolution.

On the other hand, we are at present unable to provide reasonable explanation for the observed heterogeneity with respect to many analytical dimensions. Concerning the autoregressive nature of growth process, for instance, its sectoral specificity can come from many distinct plausible sources, like for instance the effect of economic cycle, the sector lifecycle, the dynamics of relative prices or shocks in the demand. The AR structure with a time horizon of several years can be indeed more affected by macroeconomics shocks or prices movements, effects that play a minor role in the intra year dynamics shaping the growth rates density. Our time series are not long enough to allow a macroeconomics analysis of the different sectors, but this would surely constitute a relevant addition to the present analysis.

Another interesting extension of the present work is constituted by the analysis of the degree of heterogeneity of single firms inside a given sector. In this paper, consistently with the Gibrat and Simon tradition, we considered firms as different realization of the same stochastic process. Maybe, this assumption can conceal interesting differences in firms behavior. Again, the major obstacle in pursuing this line of research rests in the need of having quite long time series for a quite large number of firms, requirement that are not satisfied by our present data.

Finally, the work presented provids supporting evidence for the limitations of investigating aggregated data only. The degree of heterogeneity of the results for different sectors hint at a rich economic structure that is hidden by aggregated analysis, but that can be recovered when sectoral data are investigated.

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