Growing like mushrooms? Sectoral evidence from four large European economies

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Growing like mushrooms? Sectoral evidence from four large European economies

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Abstract This paper follows a stream of literature on the empirics of sectoral growth rates, originated by Castaldi and Dosi (Income levels and income growth. Some new cross-country evidence and some interpretative puzzles. LEM Working Paper 2004-18, Sant’Anna School of Advanced Studies, Pisa, Italy, 2004) on two-digit international manufacturing and service sectors, and by Sapio and Thoma’s (The growth of industrial sectors: theoretical insights and empirical evidence from U.S. manufacturing. LEM Working Paper 2006-09, Sant’Anna School of Advanced Studies, Pisa, Italy, 2006) study on four-digit U.S. manufacturing industries. Our aim is to discuss the statistical properties of growth rates in light of a ‘mushroom vision’ of growth. In our analysis, we focus on the growth of value added in NACE five-digit sectors in France, Germany, Italy and the United Kingdom between 1995 and 2003. We find that the volatility of sectoral growth rates is negatively correlated with sectoral size, according to a power law, but with steeper slopes than for firms and

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U.S. sectors. Rescaled sectoral growth rates are well-described by a Laplace distribution in most years. The outcomes of this statistical analysis provide a further empirical foundation to a view of sectoral growth, wherein inter-firm correlations, market concentration, and inter-sectoral feedbacks play a major role.

**Keywords** Sectoral growth · Subbotin distribution · Scaling · Manufacturing · Europe

**JEL Classification** C10 · O47 · O51

1 **Introduction**

How the sectoral structure of an economy evolves and how sectoral inter-dependencies unfold are central research themes in economics. Rosenberg’s (1976) observations on the technological convergence of U.S. manufacturing industries and the more recent analysis of General Purpose Technologies (GPT) have fostered a host of investigations on the properties of growth led by common drivers.\(^1\) The presence of technological interdependencies between sectors may suggest that eventually the dynamics of sectors will closely co-evolve, and that convergence will take place - as in Harberger’s (1998) “yeast vision”. However, coordination problems and the need for complementary investments may slow the diffusion of new technologies, as stressed in the analysis on the emergence of new *techno-economic paradigms*.\(^2\) Together with heterogeneity in adoption rates and absorption lags, a high concentration of sectoral growth rates is to be expected, supporting the so-called “mushroom vision” of growth (Harberger 1998). According to this view, real cost reductions in the economy stem from a large number of different sources, but just a few sectors contribute with a disproportionate share to the overall dynamics. Hence, common drivers of growth play a minor role. Schumpeter would probably embrace this view, which is very much based on the impact of *creative destruction*.

The present work contributes to the yeast-mushroom debate by analyzing the distributional properties of a cross-section of 1-year and 5-year sectoral value added growth rates for France, Germany, Italy and the United Kingdom, for the period 1995–2003. We find that the variance of sectoral growth rates is negatively correlated with sectoral size, meaning that the growth performances of smaller sectors are more heterogeneous. Small sectors thus account for a larger share of the overall cross-sectoral growth variance. As a result, growth rates are unevenly spread - a finding which is consistent with the mushrooms

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\(^1\)See Bresnahan and Trajtenberg (1995) for a definition of the GPT concept.

\(^2\)An introduction is found in Freeman and Perez (1988) and further developments in Freeman and Louca (2001). See also the historical analyses in Rosenberg (1982) and David (1990, 2000). In fact, the conceptualizations of GPT and techno-economic paradigms bear strong similarities.
view. Sectoral 1-year growth rates are well-described by a heavy-tailed Laplace distribution, a result which is robust to variance rescaling. Some cross-country differences appear with respect to 5-year growth rates, with Italy and France keeping their long-tailed nature over the medium-long run. The analysis of sectoral groups reveals that heterogeneity in technological intensities can only partly account for the detected fat tails. Although heavy tails are consistent with a vision of growth concentrated in few sectors, it is suggested that processes of firm turnover and growth by incumbents are at least partly governed by reinforcing dynamics embedded in sectoral interdependencies. This casts doubts on the validity of the pure mushrooms vision, which largely neglects the importance of common drivers of growth.

Previous contributions in this line of research include Castaldi and Dosi (2004) and Sapio and Thoma (2006). The former analyzed value added data for two-digit manufacturing sectors in 16 countries and showed that the cross-sectoral distribution of 2-year sectoral growth rates is well-described by a Laplace distribution, with few cross-country differences in shape and width. The latter studied the growth of U.S. four-digit sectoral value added and value of shipments between 1959 and 1996. Their results showed that 1-year sectoral growth rates are distributed according to heavy-tailed Subbotin distributions, with shape coefficients between 1.0 and 1.5. Moreover, the variance of growth rates scales as a power law of size with a scaling exponent between $-0.20$ and $-0.10$. Worth mentioning also is the paper by Napoletano et al. (2006), showing that concentration in sectoral contributions to aggregate productivity growth can occur even under a pure yeast process, provided that absorptive capacities are heterogeneous.

The paper is structured as follows. In Section 2, we describe the dataset and the relevant variables. In Section 3, we estimate volatility-size scaling relationships and fit the empirical densities of sectoral growth rates. Results are summarized and discussed in the concluding Section 4.

### 2 Data and variables

This work exploits data drawn from the Eurostat “Industry, Trade and Services” statistical databank (source: Eurostat 2006). The dataset under consideration covers NACE five-digit manufacturing industries, excluding mining and extraction sectors (NACE codes from da1511 to dn3663). More specifically, we use the following samples: 179 Italian sectors from 1995 to 2003; 208 German sectors for the period 1999–2003; 169 for UK between 1996 and 2003; and 166 in France between 1997 and 2003. All data are annual.$^3$

As a measure of sectoral size, we have chosen the value added evaluated at factor costs. Data have been deflated by using the sectoral deflators provided

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$^3$Cross-country differences in terms of sample sizes and time windows are due to missing values.
by Eurostat (specifically, the so-called PRIN - Domestic output price index; base year: 2000). The variables under analysis are the normalized logarithmic sectoral size,

\[ s_{it} = \log S_{it} - \langle \log S_{it} \rangle_t \]  

(1)

where \( \langle . \rangle_t \) denotes an average at time \( t \) across sectors (which are denoted by the subscript \( i \)), and 1-year sectoral growth rates:

\[ g_{it} = s_{it} - s_{i,t-1} \]  

(2)

Because particularly high or low annual growth rates may be the result of short-term fluctuations and may average out on longer horizons, we also analyze 5-year growth rates. Given the short time series available, this seems the only meaningful way to define growth rates on a time span longer than 1 year. Five-year sectoral growth rates are defined as

\[ g_{5it} = s_{it} - s_{i,t-5} \]  

(3)

The above variables have zero mean by definition. Normalization is performed in order to wash away common trends.

3 Empirical evidence

In this section, the empirical evidence on the whole sample properties of sectoral growth rates is illustrated. A description of the main statistical properties is followed by investigations on scaling properties and by Subbotin distribution fit exercises.

3.1 Basic statistical properties

We first report on the basic distributional properties of our variables. We use Kolmogorov-Smirnov (KS) tests to compare the empirical distributions of the variables of interest with normal distributions.

The KS tests performed using the logarithm of sectoral value added do not reject the assumption of normality: this can be seen as evidence of Lognormal sectoral size. The only exception comes from the Italian data, but only for the years 1996–1998. After 1998, the overall picture is similar across countries and is also in line with the U.S. sectoral evidence provided by Sapio and Thoma (2006).7

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4When missing, the deflator for a five-digit sector has been replaced by the deflator for the corresponding four-digit aggregate.
5For Germany, only 4-year growth rates can be calculated due to data constraints.
6Not reported here, available upon request.
7This evidence is consistent with the idea that right-skewed distributions in corporate size (Dosi 2005) are preserved at a higher aggregation level.
For 1-year growth rates, the assumption of normality of the underlying distribution is strongly rejected, except for England in the period 1997–2000 and for Germany and Italy in 2003. Complementary analyses, reported at length in Castaldi and Sapio (2006), show that skewness and kurtosis values have fluctuated wildly in all countries, but always in the range of heavy-tailed distributions. These patterns might indicate that growth rate distributions are not strong-form stationary. By comparing growth rate distributions for all possible couples of years, KS tests (not reported here) confirm this: the null hypothesis - identical distributions - is rejected for most of the years. The results differ across countries, but overall confirm the need for a year-by-year analysis. This is in line with the findings in Sapio and Thoma (2006).

The results of KS normality tests for the 5-year growth rates differ significantly across countries. Deviations from the Gaussian law are only detected for Italian and French distributions.

3.2 Variance-size scaling

As a first way to assess Harberger’s claim of mushroom-like growth processes, we ask whether the manufacturing structural change undergone by the economies under focus was concentrated in a few industries - as predicted by the mushrooms vision - or widely diffused, in a yeast fashion.

The existence of a time-changing pattern of cross-sectoral variation in growth performances can be seen as a sign of structural change. Metcalfe et al. (2006) detected the structural trasformation of U.S. manufacturing by looking at the time evolution of the Herfindahl index for sectoral employment shares. A time-constant concentration degree requires all sectors to grow at the same rate. Any growth heterogeneity engenders changes in the sectoral composition of the manufacturing output. The higher the growth rates variance, the faster the structural change.

Whether change is concentrated in few sectors can be assessed by comparing the dispersion of growth rates across groups. If change is diffused, as could be the case in a yeast process, different groups of sectors should all account for approximately the same share of the total variance. A mushroom story requires that some groups contribute more to the overall change. Here we compare variances across size groups. The underlying assumption is that the growth rates of industries are more or less heterogeneous, depending on whether industries are large or small.

The evidence on industry life-cycles (Gort and Klepper 1982; Klepper and Graddy 1990) supports this assumption. According to the industry lifecycle view, large and mature industries converge to an oligopolistic structure, characterized by price-cost competition and very low turbulence. The limited firm turnover and the narrow opportunities for product improvements make

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8Similarly, Harberger’s quasi-Lorenz curves measure contributions to aggregate real cost reduction according to size classes.
Table 1  Estimated power-law scaling coefficients and standard errors, for value added 1-year log-growth rates: binned OLS regression (20 bins), nonlinear LS, nonlinear LAD

| Countries | Years | Binned OLS $\hat{\beta}$ | Nonlinear LS $\hat{\beta}$ | Nonlinear LAD $\hat{\beta}$ |
|-----------|-------|---------------------------|-----------------------------|-----------------------------|
| France    | 1998  | $-0.3290$ (0.1307)        | $-0.3231$ (0.1306)          | $-0.2539$ (0.0235)          |
|           | 1999  | $-0.0613$ (0.1068)        | $-0.3094$ (0.0998)          | $-0.2815$ (0.0196)          |
|           | 2000  | $-0.1326$ (0.1141)        | $-0.1722$ (0.0833)          | $-0.1887$ (0.0221)          |
|           | 2001  | $-0.1904$ (0.1312)        | $-0.1458$ (0.1075)          | $-0.2046$ (0.0202)          |
|           | 2002  | $-0.1864$ (0.0918)        | $-0.2681$ (0.0670)          | $-0.2577$ (0.0272)          |
|           | 2003  | $-0.2863$ (0.1018)        | $-0.2908$ (0.0909)          | $-0.2890$ (0.0306)          |
| Germany   | 2000  | $-0.1877$ (0.0854)        | $-0.2048$ (0.0512)          | $-0.1909$ (0.0199)          |
|           | 2001  | $-0.2173$ (0.0668)        | $-0.1940$ (0.0468)          | $-0.1906$ (0.0190)          |
|           | 2002  | $-0.3490$ (0.0679)        | $-0.3194$ (0.0497)          | $-0.3226$ (0.0240)          |
|           | 2003  | $-0.0678$ (0.0340)        | $-0.0593$ (0.0377)          | $-0.0667$ (0.0193)          |
| Italy     | 1996  | $-0.3462$ (0.1223)        | $-0.2374$ (0.0731)          | $-0.2133$ (0.0214)          |
|           | 1997  | $-0.2733$ (0.0865)        | $-0.2178$ (0.0468)          | $-0.2429$ (0.0217)          |
|           | 1998  | $-0.3273$ (0.0930)        | $-0.2515$ (0.0532)          | $-0.2589$ (0.0212)          |
|           | 1999  | $-0.3075$ (0.0989)        | $-0.3051$ (0.0672)          | $-0.2441$ (0.0215)          |
|           | 2000  | $-0.2574$ (0.0913)        | $-0.2562$ (0.0584)          | $-0.2885$ (0.0206)          |
|           | 2001  | $-0.3046$ (0.0881)        | $-0.2597$ (0.0630)          | $-0.2694$ (0.0232)          |
|           | 2002  | $-0.1203$ (0.1105)        | $-0.1549$ (0.0664)          | $-0.2020$ (0.0208)          |
|           | 2003  | $-0.2973$ (0.0698)        | $-0.2572$ (0.0501)          | $-0.2470$ (0.0254)          |
| UK        | 1997  | $-0.2532$ (0.0796)        | $-0.2649$ (0.0772)          | $-0.2379$ (0.0298)          |
|           | 1998  | $-0.1695$ (0.0917)        | $-0.1753$ (0.0711)          | $-0.1972$ (0.0289)          |
|           | 1999  | $-0.3211$ (0.0546)        | $-0.3060$ (0.0518)          | $-0.3173$ (0.0297)          |
|           | 2000  | $-0.3008$ (0.0703)        | $-0.2533$ (0.0643)          | $-0.2604$ (0.0305)          |
|           | 2001  | $-0.2551$ (0.0609)        | $0.0706$ (0.1059)           | $-0.0551$ (0.0222)          |
|           | 2002  | $-0.2902$ (0.1046)        | $-0.2589$ (0.0759)          | $-0.2822$ (0.0299)          |
|           | 2003  | $-0.1966$ (0.0846)        | $-0.2190$ (0.0608)          | $-0.2315$ (0.0278)          |

Time span: 1996-2003

large sectoral growth performances very similar. Smaller sectors in early stages of the life-cycle may instead be characterized by widely diverse patterns of entry and exit. Entry flows may decline constantly since the inception, or peak during the life-cycle, only to decrease afterwards. Industries may or may not experience shakeouts. The extent of opportunities for technical innovation and appropriability can vary considerably across growing industries, depending on technological regimes (see Dosi 1982, 1988; Winter 1984; Audretsch 1995).

On these grounds, we expect the growth of small sectors to be more heterogeneous than for large ones. A simple way to model this is to assume that the cross-sectoral growth variance depends on sectoral size, according to a power law with parameters $k$ and $\beta > 0$.\(^9\)

$$
\sigma^2(g_{it}|S_{t,t-1}) = kS_{t,t-1}^{-2\beta}
$$

\(^9\)This equation has been estimated in firm growth empirics. Estimates of the exponent $\beta$ lay in the range ($-0.20, -0.15$) for data on U.S. companies (Stanley et al. 1996; Amaral et al. 1997). The evidence of scaling in Italian (Bottazzi and Secchi 2003) and French data (Bottazzi et al. 2005) is much less compelling.
Empirical estimates of the variance-size relationship are provided according to two alternative approaches: linear regression on binned variables, and non-linear regression. Within the former methodology, for each country and for any given year, the values of sectoral size are binned in equipopulated groups, and standard deviations of the associated 1-year growth rates are computed. Next, for each country, the power-law coefficients are estimated by regressing the log-standard deviations on the mean logarithm size of that country’s sectors within the corresponding bins:

$$\log \sigma_t = \alpha + \beta \log S_{t-1} + \epsilon_t$$  \hspace{1cm} (5)

A more refined estimation technique for the same relation takes the following model as a starting point:

$$s_t - s_{t-1} = e^{\beta s_{t-1}} \epsilon_t$$  \hspace{1cm} (6)

and estimates $\beta$ via non-linear regression, using numerical methods based on different optimization criteria, depending on the underlying assumptions about the i.i.d. error term $\epsilon_t$: (i) non-linear LS if $\epsilon_t \sim \text{Normal}$; (ii) non-linear LAD (Least Absolute Deviation) if $\epsilon_t \sim \text{Laplace}$ (cf. Bottazzi et al. 2005).

Table 1 displays the values of the scaling exponent, country by country and year by year, for deflated value added 1-year growth data. Each box

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**Fig. 1** Scatterplot of the log-standard deviation of growth rates vs. log-size, and linear OLS regression fit, for (clockwise): France 1998 ($\beta = -0.3290$), Germany 2001 ($\beta = -0.217$), Italy 1998 ($\beta = -0.3273$), and the U.K. 2000 ($\beta = -0.3008$). Estimates are based on a 20-bins binning procedure.
reports: in the first column, estimates of $\beta$ from Eq. 5 based on linear OLS on binned data; in the second and third, respectively, the $\beta$ estimated by non-linear LS and non-linear LAD under the model in Eq. 6. Standard errors are also included. Figure 1 provides a graphical illustration of the estimated OLS scaling relations.

Results are quite similar across countries. Scaling exponents are virtually always negative, suggesting that the variance of sectoral growth declines with sectoral size. More specifically, the binned OLS point estimates of $\beta$ are in the range $(-0.06, -0.33)$ for France, $(-0.07, -0.35)$ for Germany, $(-0.12, -0.35)$ for Italy, and $(-0.17, -0.32)$ for the U.K. Estimates are more stable across years under the non-linear LS estimation, but confidence intervals are still quite large. Assuming Laplace heavy-tailed disturbances considerably improves the estimation performance. Non-linear LAD estimates are much more precise and yield smaller ranges of variation: $(-0.19, -0.29)$ for France, $(-0.07, -0.32)$ for Germany, $(-0.20, -0.29)$ for Italy, and $(-0.20, -0.32)$ for the U.K. The better performance of the LAD estimator makes sense in view of the upcoming results on distributional shapes.

The results reported in Table 2 confirm the existence of a significant negative scaling relation between 5-year growth rates and size, although milder than for 1-year growth rates. This cross-sectoral variance pattern is clearer for Italy and France, less so for Germany and the UK.

We conclude that large sectors are less heterogeneous than smaller ones in all of the 4 large European economies under consideration. Scaling relationships tend to be slightly steeper than those observed by Sapio and Thoma (2006) on U.S. data, and hold over longer time spans. This is in line with the observed persistence of intersectoral differences in innovation opportunities and turnover rates (Dunne et al. 1988). Scaling slopes are always well below zero, meaning that small sectors account for a disproportionate share of the overall manufacturing structural change. Hence, sectoral growth rates are unevenly spread. This is consistent with the mushroom view of growth.

### Table 2  Estimated power-law scaling coefficients and standard errors, for value added 5-year log-growth rates: binned OLS regression (20 bins), nonlinear LS, nonlinear LAD

| Countries | Years       | Binned OLS $\hat{\beta}$ | Nonlinear LS $\hat{\beta}$ | Nonlinear LAD $\hat{\beta}$ |
|-----------|-------------|----------------------------|-----------------------------|-------------------------------|
| France    | 1997–2002  | $-0.1642 (0.0607)$         | $-0.1814 (0.0538)$          | $-0.1927 (0.0408)$            |
|           | 1998–2003  | $-0.1890 (0.0775)$         | $-0.2295 (0.0459)$          | $-0.2611 (0.0331)$            |
| Germany   | 1999–2003  | $-0.0474 (0.0508)$         | $-0.0544 (0.0372)$          | $-0.0592 (0.0294)$            |
| Italy     | 1995–2000  | $-0.2382 (0.0745)$         | $-0.1907 (0.0471)$          | $-0.2291 (0.0353)$            |
|           | 1996–2001  | $-0.2281 (0.0618)$         | $-0.2609 (0.0460)$          | $-0.2775 (0.0336)$            |
|           | 1997–2002  | $-0.2070 (0.0750)$         | $-0.1415 (0.0331)$          | $-0.2401 (0.0231)$            |
|           | 1998–2003  | $-0.1543 (0.0957)$         | $-0.1454 (0.0378)$          | $-0.2097 (0.0265)$            |
| UK        | 1996–2001  | $-0.1553 (0.0915)$         | $-0.0395 (0.0632)$          | $-0.0999 (0.0467)$            |
|           | 1997–2002  | $-0.1555 (0.0943)$         | $-0.0622 (0.0629)$          | $-0.0721 (0.0472)$            |
|           | 1998–2003  | $-0.1729 (0.0704)$         | $-0.1666 (0.0599)$          | $-0.1789 (0.0485)$            |

Time span: 1996-2003
3.3 The distribution of sectoral growth rates

The present section deals with the cross-sectoral distribution of sectoral growth rates, for each country and for each year of the available samples. This is a crucial step towards understanding the nature of the sectoral growth process. In a pure yeast process, growth rates would be randomly dispersed around the mean. In a mushroom perspective, most of the dynamics in the cross-section of industries would be accounted for by the growth of a few industries, while the bulk would stagnate. In the probability density function, this would show up as a sharp peak around the modal value, and fat tails.

These are features of the exponential power distribution fitted by Bottazzi and Secchi (2006) on growth rates of business firms. As the authors have shown, reinforcing dynamics is a key to the emergence of exponential tails. Their model can be adapted to sectoral growth by assuming that a limited number of shocks are distributed across sectors, and that if a sector is affected by a shock, its likelihood to collect further shocks increases. Shocks can determine turbulence in a sectoral ecology, as well as growth or decline by incumbents. The process at hand is characterized by increasing returns, and can be fueled by the sheer internal dynamics of a sector, as well as by sectoral correlations and interdependencies.

Sector-specific drivers of increasing returns are closely related to the waves of Schumpeterian creative destruction brought about by new cohorts of entrants. According to the so-called displacement effect (Carree and Thurik 1999), the entry of an innovative firm can force some incumbents to exit the market because of technological obsolescence. Due to this effect, a sector affected by a growth event in the form of entry is more likely to collect a further event - a firm’s exit. The opposite occurs via the replacement effect, i.e. entry enabled by exit. Similar dynamics apply if firms play a coevolutionary game with competitors, as in March (1994). Search for innovation is triggered by a firm’s performance falling below a certain aspiration threshold - but successful search can adversely affect competitors, forcing them to start a search process, too. Growth shocks to a firm - such as innovative search outcomes - increase the likelihood that other firms in the same industry seize innovational opportunities. In this case, as well as in the one described earlier, large swings in sectoral size tend to be concentrated in a small, yet non-negligible, number of industries.

Sectoral interdependencies provide many examples of how heavy tails can emerge in sectoral growth. First, a GPT economy enjoys increasing returns due to horizontal and vertical externalities (Bresnahan and Trajtenberg 1995). Any improvement in the upstream sector’s technology creates incentives for

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10Indeed, most entry results in exit, first by small, young incumbents and recent entrants, and eventually by most of the entrants themselves: see Geroski (1995), Disney et al. (2003), Bartelsman et al. (2005).

11See Carree and Thurik (1999) again.
downstream firms to invest in complementary knowledge. This in turn opens up further innovation opportunities for upstream producers. More generally, the probabilities of fast growth for partner firms in different sectors tend to go together, and sectors may grow or stagnate in a rather coordinated and lumpy fashion. **Second**, incumbents react to entry in a selective way (Geroski 1995), i.e. mainly to entrants diversifying from other sectors, which are on average larger and more likely to survive than *de novo* entrants (Dunne et al. 1988), and can build on experience in related industries (Klepper 2002). Cross-sectoral similarities in knowledge bases enable entry via diversification, which in turn triggers a chain of reactions by incumbents, implying an increased sectoral likelihood to collect growth shocks. **Third**, suppose there exists a fixed stock of potential entrants, and that entry in a sector signals the existence of wide and unexploited opportunities for innovation. Then, entry by a firm might increase the sectoral probability to attract even more potential entrants. A long right tail may emerge in the sectoral growth distribution - as observed by Geroski (1995), entry comes in bursts. **Finally**, exit by a customer, a supplier or a partner can decrease the chances of survival for the partner firms that belong to other sectors. This may give rise to a fat left tail, because sectors with a large negative growth rate would always be lumped together.

To sum up: on the one hand, finding evidence of heavy-tailed distributions of sectoral growth rates is consistent with the mushroom view of sectoral-specific, concentrated drivers of change. On the other hand, heavy tails are also a sign of sectoral interdependencies and common components, which the mushrooms view tends to discard.

The empirical density of sectoral growth rates $g_{it}$ and $g_{5it}$ is modeled by means of the power-exponential or Subbotin family (Subbotin 1923), which was first introduced into economics by Bottazzi and Secchi (2003). The Subbotin probability density function reads:

$$f(g_{it}) = \frac{1}{2ab^{1/b} \Gamma \left(1 + \frac{1}{b}\right)} e^{-\frac{1}{b} \left(\frac{|g_{it} - \mu|}{\sigma}\right)^b}$$

(7)

where $b$ is a shape parameter, and $\Gamma(.)$ is the gamma function. The Subbotin reduces to a Laplace if $b = 1$, and to a Gaussian if $b = 2$.12 As $b$ gets smaller, the tails become heavier, and the density peak gets sharper. This model has been chosen because it provides a generalization of both the benchmark Normal distribution and the Laplace law, which was shown to provide an excellent fit to the empirical density function of corporate growth rates by Bottazzi and Secchi (2003, 2006).

This given, for each country we run a Maximum Likelihood estimation procedure for each available year.13 The estimated shape coefficients $b$ of the

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12Further cases are: degenerate ($b = 0$), and Continuous Uniform ($b = \infty$).

13In light of the negative result on strong-form stationarity, we prefer not to pool observations across years. Estimates are done using the Subbotools developed by Giulio Bottazzi (see Bottazzi 2004 for documentation).
Subbotin for 1-year growth rates are reported in the upper layers of Table 3, along with standard errors. Figure 2 shows the fit of the estimated Subbotin distribution with respect to the empirical densities.

Italian point estimates of the shape coefficient are scattered around the Laplace value of 1 (more precisely, between 0.70 and 1.12). The UK results for the shape coefficient are also similar, ranging between 0.86 and 1.28. German estimates are between 0.75 and 0.92, except for the last year, 2003, when the shape parameter is 1.83. This indicates a high degree of normality of the distribution. France represents somewhat an exception to the Laplace pattern: estimates of $b$ are systematically below 1, except in 2001.

As shown by the scaling analysis, the variance of sectoral growth rates depends on the sectoral size. Therefore, the i.i.d. assumption does not hold, and the evidence of heavy tails in sectoral growth may be a statistical artifact due to the mixture of different, possibly non-heavy-tailed processes. In order to control for cross-sectoral heteroskedasticity, we fit the empirical density functions of the following rescaled version of sectoral growth rates:

$$\tilde{g}_{it} = \frac{g_{it}}{e^{\hat{\beta}_{it-1}}}$$  \hspace{1cm} (8)

where $\hat{\beta}$ is the scaling exponent estimated through non-linear LAD, so that $\tilde{g}_{it}$ actually corresponds to the estimated residual from Eq. 4. Table 3 (top) shows that, although Subbotin shape coefficients for rescaled growth rates are slightly higher than before rescaling, differences in point estimates are rather small, and the heavy-tailed nature of sectoral growth holds.

More in detail, Italian $b$ values are between 0.85 and 1.35; French ones in the range (0.70, 0.85); German shape coefficients vary in the interval 0.96 - 1.10; and similarly for the UK (0.98, 1.12). See also the diagrams in Fig. 2. Two exceptions to these general pattern are worth noting. Growth rates for Germany in 2003 and the U.K. in 1999 are very close to Gaussian. Again, French sectoral dynamics displays a peculiar behavior, with $b$ values below 1, except in 2001. Notwithstanding these exceptions, fat tails in sectoral growth processes seem to reveal some more fundamental economic mechanism, beyond statistical aggregation phenomena. Results of this section tend to be in line with the results of U.S. manufacturing sectors and, interestingly, also with the firm-level evidence.

The estimated parameters in Table 3 (bottom) for 5-year growth rates and their rescaled versions indicate that the distributions have exponential tails for Italy and France, while their tails are rather normal for Germany.
**Table 3** Estimated Subbotin coefficients, for sectoral value-added 1-year and 5-year logarithmic growth rates ($g$, $g^5$) and rescaled ones ($\tilde{g}$, $\tilde{g}^5$) using power laws estimated by nonlinear LAD

| Years | France | Germany | Italy | UK |
|-------|--------|---------|-------|----|
|       | $\hat{b}$ | $\hat{a}$ | $s_b$ | $s_a$ | $\hat{b}$ | $\hat{a}$ | $s_b$ | $s_a$ | $\hat{b}$ | $\hat{a}$ | $s_b$ | $s_a$ | $\hat{b}$ | $\hat{a}$ | $s_b$ | $s_a$ |
| $g$   |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1996  | 0.5279 | 0.0660 | 0.0812 | 0.0096 | 0.7604 | 0.1306 | 0.0999 | 0.0135 | 1.0410 | 0.1463 | 0.1458 | 0.0137 | 1.2244 | 0.1834 | 0.0141 | 0.0013 |
| 1997  | 0.6391 | 0.0702 | 0.1012 | 0.0096 | 0.7604 | 0.1306 | 0.0999 | 0.0135 | 0.6999 | 0.1209 | 0.0906 | 0.0128 | 1.0349 | 0.1658 | 0.0115 | 0.0012 |
| 1998  | 0.7841 | 0.0912 | 0.1287 | 0.0116 | 0.9198 | 0.1258 | 0.0081 | 0.0008 | 0.8352 | 0.1598 | 0.1117 | 0.0160 | 0.8990 | 0.1561 | 0.0096 | 0.0012 |
| 1999  | 1.3742 | 0.1152 | 0.2557 | 0.0125 | 0.8115 | 0.1138 | 0.0069 | 0.0007 | 0.9699 | 0.1574 | 0.1338 | 0.0151 | 1.0268 | 0.1923 | 0.0114 | 0.0014 |
| 2000  | 0.6393 | 0.0712 | 0.1013 | 0.0097 | 0.7494 | 0.1105 | 0.0063 | 0.0007 | 0.6971 | 0.1195 | 0.0902 | 0.0127 | 0.8860 | 0.1669 | 0.0095 | 0.0013 |
| 2001  | 0.9103 | 0.0746 | 0.1539 | 0.0091 | 1.8287 | 1.6126 | 0.0191 | 0.0085 | 1.1230 | 0.1578 | 0.1601 | 0.0145 | 0.8575 | 0.1355 | 0.0091 | 0.0011 |
| $\tilde{g}$ |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1996  | 0.8814 | 0.1591 | 0.1085 | 0.0143 | 1.1561 | 0.1344 | 0.1510 | 0.0112 | 1.1362 | 0.1400 | 0.1478 | 0.0169 | 1.1237 | 0.1659 | 0.0127 | 0.0012 |
| 1997  | 0.7268 | 0.0717 | 0.0984 | 0.0078 | 0.9259 | 0.1269 | 0.1151 | 0.0112 | 0.7325 | 0.0736 | 0.0993 | 0.0079 | 2.1015 | 0.2029 | 0.0282 | 0.0013 |
| 1998  | 0.7687 | 0.0736 | 0.1051 | 0.0079 | 0.9831 | 0.1122 | 0.0950 | 0.0081 | 1.1640 | 0.1585 | 0.1523 | 0.0132 | 1.0388 | 0.1582 | 0.0115 | 0.0012 |
| 1999  | 0.6976 | 0.0796 | 0.0937 | 0.0088 | 0.9450 | 0.1138 | 0.0833 | 0.0007 | 0.7684 | 0.0872 | 0.1051 | 0.0100 | 1.0665 | 0.1902 | 0.0111 | 0.0014 |
| 2000  | 0.7108 | 0.0679 | 0.0958 | 0.0075 | 0.9566 | 0.1105 | 0.0850 | 0.0007 | 0.8258 | 0.1221 | 0.1003 | 0.0112 | 1.0254 | 0.1677 | 0.0113 | 0.0013 |
| 2001  | 0.7687 | 0.0736 | 0.1051 | 0.0079 | 0.9831 | 0.1122 | 0.0950 | 0.0081 | 1.1640 | 0.1585 | 0.1523 | 0.0132 | 1.0388 | 0.1582 | 0.0115 | 0.0012 |
| 2002  | 0.8517 | 0.0795 | 0.1198 | 0.0082 | 1.9439 | 1.6126 | 0.0207 | 0.0085 | 1.3543 | 0.1483 | 0.1840 | 0.0118 | 0.9789 | 0.1374 | 0.0107 | 0.0010 |
| $\tilde{g}^5$ |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1995-2000 |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1996-2001 |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1997-2002 | 1.2297 | 0.2585 | 0.1860 | 0.0241 | 0.8404 | 0.2452 | 0.1025 | 0.0224 | 1.0388 | 0.3305 | 0.1976 | 0.0301 | 1.1978 | 0.3293 | 0.1976 | 0.0301 |
| 1998-2003 | 0.8867 | 0.2188 | 0.1246 | 0.0224 | 1.9430 | 1.6688 | 0.2978 | 0.1254 | 0.8254 | 0.2264 | 0.1003 | 0.0207 | 1.3565 | 0.3583 | 0.2084 | 0.0323 |
| $\tilde{g}^5$ |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1995-2000 |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1996-2001 |        |        |       |      |        |        |       |      |        |        |       |      |        |        |       |      |
| 1997-2002 | 1.0922 | 0.2999 | 0.1606 | 0.0289 | 0.8131 | 0.2159 | 0.0985 | 0.0199 | 1.3241 | 0.3685 | 0.2022 | 0.0334 | 1.6945 | 0.4189 | 0.2767 | 0.0359 |
| 1998-2003 | 0.8671 | 0.3304 | 0.1213 | 0.0347 | 1.9249 | 1.6612 | 0.2942 | 0.1251 | 0.8419 | 0.2125 | 0.1027 | 0.0194 | 1.6945 | 0.4189 | 0.2767 | 0.0359 |
Fig. 2  Empirical density and Subbotin fit, value added growth rates for (clockwise): France 2003 ($b = .8517$), Germany 2001 ($b = .9450$), the U.K. 2000 ($b = 1.0388$) and Italy 2001 ($b = 1.2228$)

and UK. These results match the KS test discussed earlier.\textsuperscript{16} Given that for each country only one or a couple of distributions can be studied, it seems difficult to advance explanations of these cross-country differences. Still, one could think of country-level factors such as national policies promoting specific sectoral activities in a targeted way as reasons behind higher probabilities for particularly high and sustained growth rates. At the same time, the evidence of Laplacian distributions on longer time spans should not come as a surprise if the main driver of heavy tails lies in the pattern of inter-sectoral correlations at the heart of national economies. These correlations can be seen as structural properties of the economic system and they are likely to show high stickiness, although they may change on even longer time horizons.

\textsuperscript{16}It is instructive to compare this evidence with the firm level results in Bottazzi and Secchi (2006): firm growth rates on longer time spans become more normal but the estimated Subbotin parameters always remain below 2. They point out to the fact that normality would be observed if annual growth rates were i.i.d. realizations, but auto-correlation in time indicates that this is not the case. This is in line with a view of growth where path-dependence plays an important role.
3.4 Conditioning on technological intensity

The results so far suggest the existence of a strong cross-sectional heterogeneity in growth performance, with very high growth rates co-existing with very low ones. We wish to check the robustness of these results by performing the same analysis on more homogeneous groups of sectors. In particular, we divide sectors according to the OECD Technology Classification. Such a classification ranks sectors based on the level of their R&D intensity in value added and production estimated in a sample of OECD countries (see Hatzichronoglou 1997). This classification is meant to capture different degrees of “knowledge intensity” of production (cf. OECD 2005). R&D expenses are a proxy for overall innovation efforts and can also be seen as an indicator of the level of technological opportunities in the industry (cf. Nelson and Wolff 1997). This classification has become quite popular because it captures in its High Tech group most of the backbone sectors of the ICT production.

We mentioned in the introduction how GPTs could be seen as bringing overall productivity increases across industries. Still, if this process takes some

| Table 4 | Estimation results for binned scaling and Subbotin fit, High and High medium tech sectors vs Low and Low medium tech sectors: France and Germany |
|---|---|---|---|---|---|
| France | | | | | |
| High tech and high medium tech | Scaling | $\beta$ | $sd(\beta)$ | $R^2$ | Subbotin | $b$ | $sd(b)$ |
| 1998 | 0.1170 | 0.2280 | 0.0318 | 1998 | 1.2516 | 0.3736 |
| 1999 | 0.0968 | 0.2829 | 0.0144 | 1999 | 0.8772 | 0.2417 |
| 2000 | 0.1734 | 0.2285 | 0.0671 | 2000 | 0.6856 | 0.1805 |
| 2001 | 0.4170 | 0.2820 | 0.2949 | 2001 | 1.0401 | 0.2972 |
| 2002 | 0.5904 | 0.2727 | 0.3694 | 2002 | 0.5657 | 0.1444 |
| 2003 | 0.2690 | 0.2295 | 0.1466 | 2003 | 1.0654 | 0.3061 |
| 1997–2002 | 0.0129 | 0.1244 | 0.0013 | 1997–2002 | 1.5442 | 0.4869 |
| 1998–2003 | 0.0126 | 0.2815 | 0.0003 | 1998–2003 | 0.9413 | 0.2632 |
| Low tech and low medium tech | 1998 | 0.3659 | 0.2979 | 0.1587 | 1998 | 0.6378 | 0.1256 |
| 1999 | 0.1775 | 0.1439 | 0.1598 | 1999 | 0.6888 | 0.1374 |
| 2000 | 0.3003 | 0.2029 | 0.2150 | 2000 | 0.7724 | 0.1573 |
| 2001 | 0.3882 | 0.2382 | 0.2493 | 2001 | 0.7368 | 0.1487 |
| 2002 | 0.2992 | 0.1504 | 0.3222 | 2002 | 1.1855 | 0.2644 |
| 2003 | 0.3933 | 0.1045 | 0.3132 | 2003 | 0.9038 | 0.1897 |
| 1997–2002 | 0.0651 | 0.1184 | 0.0364 | 1997–2002 | 2.6948 | 0.9097 |
| 1998–2003 | 0.3500 | 0.0901 | 0.6536 | 1998–2003 | 1.7252 | 0.4250 |
| Germany | | | | | |
| High tech and high medium tech | 2000 | 0.2964 | 0.3933 | 0.2606 | 2000 | 0.8064 | 0.0270 |
| 2001 | 0.0002 | 0.2092 | 0.0000 | 2001 | 1.3275 | 0.0498 |
| 2002 | 0.3025 | 0.2529 | 0.4702 | 2002 | 1.6044 | 0.0633 |
| 2003 | 0.0655 | 0.2197 | 0.0523 | 2003 | 2.9582 | 0.1417 |
| 1999–2003 | 0.0651 | 0.1184 | 0.0364 | 1999–2003 | 2.6948 | 0.9097 |
| Low tech and low medium | 2000 | 0.2529 | 0.2352 | 0.4178 | 2000 | 1.3557 | 0.0319 |
| 2001 | 0.3423 | 0.2746 | 0.4909 | 2001 | 0.9069 | 0.0194 |
| 2002 | 0.4445 | 0.2113 | 0.7332 | 2002 | 1.0614 | 0.0235 |
| 2003 | 0.1094 | 0.1089 | 0.3852 | 2003 | 2.9981 | 0.0900 |
| 1999–2003 | 0.0916 | 0.0653 | 0.1977 | 1999–2003 | 2.7195 | 0.7272 |
time to happen, one would at least expect to find more homogeneous growth patterns in groups of sectors with comparable technology intensity.

At a first glance, results do not show a clear pattern of differences across groups. High tech sectors are in general bigger in value added than low tech
ones, but this result could be the outcome of a different classification density for the two types of industries (see the extended tables of results in Castaldi and Sapio 2006). In order to check for scaling and distributional properties, we collapsed the four groups into two in order to have enough industries in each group. Tables 4 and 5 collect results for 1- and 5-year growth rates. The evidence of a negative scaling relation remains valid in the more homogeneous groups, although it loses significance in some years, and vanishes for French and UK hi-tech industries. As for growth rates distributions, it is interesting to note that some show a higher degree of normality (the estimated Subbotin coefficients are closer to two), indicating that we may have captured some part of the reason for the exponential tails. For UK and Italy, it appears that the distribution of 1- and 5-year growth rates in the Low tech-Low medium tech group is closer to a Normal distribution, while for Germany this is the case for the High-high medium tech group. As to France, growth rates over 5 years are less heavy-tailed than over 1 year. All other distributions still display significant weight in the tails.

These preliminary results indicate that conditioning on technology intensity can only partly explain the fat tails of the unconditional distribution of growth rates. We should also mention that Sapio and Thoma (2006) classify sectors according to the Pavitt taxonomy and by the nature of the product, and they find evidence that the distributional properties of sectoral growth rates remain essentially the same in the different groups.

4 Concluding remarks

The foregoing statistical analysis of sectoral growth rates in the largest European countries has shed light on a number of facts concerning both the recent evolution of the main European economies and the phenomena underlying it. The Maximum Likelihood fit of the empirical densities shows how sectoral log-growth rates in France, Germany, Italy and the U.K. share significant non-Normality, with some support to the evidence of a Laplace distribution of sectoral growth rates. Moreover, a variance-size scaling analysis establishes that the cross-sectoral variance of sectoral growth rates is larger among small sectors. This work tends to confirm the main conclusions reached by previous analyses within the same research line, while at the same time it engenders some new and intriguing research questions. In particular, the aim of this paper has been to discuss the empirical evidence with respect to a ‘mushroom-view’ of the growth process.

First, if one considers the process of structural change underlying growth, a mushroom-like process will predict that certain groups of sectors contribute more than proportionally to the overall cross-sectoral variance of growth. What we uncover is that smaller sectors are characterized by a significantly higher variance in growth than larger sectors. The scaling relation between variance and size can be explained by insights from the literature on Industry
Life Cycles. Industries face high turbulence in their initial stages and tend then to converge in their maturity stage to oligopolistic structures with limited sources of variance in terms of entry and exit of firms.

Second, extreme fluctuations in sectoral growth rates are much more likely than under the benchmark Normal process, in spite of the aggregate nature of sectoral variables. While in a pure yeast process annual growth rates would be distributed normally, a mushroom process produces fat tails brought about by the concentration of very high and very low sectoral growth rates. The success of the mushroom description, however, is undermined by the fact that heavy tails are related to processes of firm turnover and incumbent growth, which are at least partly governed by reinforcing dynamics embedded in sectoral interdependencies. Firms in inter-related sectors can be thought of making correlated business decisions that also explain an uneven diffusion of technological and demand shocks through the economy. While heavy tails are consistent with the mushroom view, the emphasis on common drivers is at variance with it.

Third, on a longer time horizon, the properties of sectoral growth show increasing cross-country differences. While for Germany and UK there is suggestive evidence that the distributions become closer to normality, for Italy and France, 5-year growth rates still show exponential tails. In this case, the evidence suggests that sectoral interdependencies are structural properties that matter also on a longer time span. At the same time, one could think of country-specific factors which explain stronger or weaker inter-sectoral correlations of national economies. Overall, the results suggest that on a longer time horizon there may well be cross-country differences in the distributions of sectoral growth rates.

Fourth, in general the way firm-level properties aggregate to the sectoral level remains a critical area of research. The translation of firm-level scaling properties into sectoral-level volatility patterns is not as clear for European data as for U.S. manufacturing. To the authors’ knowledge, there exists no evidence about volatility-size scaling for German and U.K. companies. Moreover, it is interesting to compare the detected scaling evidence with the absence of any clear volatility-size scaling in firm-level French and Italian samples (respectively, see Bottazzi et al. 2005; and Bottazzi and Secchi 2003). Scale-invariance seems to break down in these cases. In fact, firm-level shocks may aggregate in a non-trivial way. Instead of compensating out in the aggregation process, they may amplify and produce relevant sectoral shocks. Along these lines, Gabaix (2005) shows how a major part of aggregate growth shocks can be accounted for by the growth of the top 100 firms in a country (see also the discussion in Castaldi and Dosi 2008).

Finally, in terms of how sectoral growth rates are shaped and where ‘mushrooms’ are bound to appear, much is also likely to be learned from taking into account how technological shocks diffuse in the economy, for instance through the input-output relations that link different industries. As a first step into analyzing the role of technology, we did find some weak evidence that growth rates show less fat tails within groups of homogeneous technology intensity.
These results, although very preliminary, provide a starting point for further investigations.

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